Optimal Residential House Energy Management System with Thermal Prediction

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I would like to dedicate this thesis to my loving parents and all the supervisors who helped in this project. Also I would like to thank all my work mates for their continuous help during my study.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Abstract

To achieve a higher energy efficiency and reduce CO_2 emission during the process of house energy consumption based on the fast development of smart grid and smart home infrastructures. With the help of Inteb stainability and Centre for Global Eco-innovation (CGE), this project aims to develop a cost-effective energy management solution for residential houses. To accomplish that, an Intelligent web/app based IT solution for monitoring and controlling energy in buildings is developed.

There are several outcomes from this entire solution. First of all, a building thermal model and the method to predict the temperature change for different types of buildings are proposed. This prediction takes very short time to formulate the trainer thus satisfy the plug and ready-to-use need of residential users'. This method is further used in our Web APP to help the automatic determination on house heating system operation. Then, a load scheduling optimisation algorithm has been developed to schedule the devices and appliances for domestic buildings, in order to minimise the energy cost for users while satisfying their comfort level. This algorithm takes day-ahead pricing from energy retailers and similar day energy consumption data into account. Users can predefine their preferred room temperature and appliances execution time. The exhaustive search method is used to solve the optimisation problem with optimal performance. The result shows higher energy efficiency than the previous method. Over 15% of energy consumption reduction is achieved with optimal load scheduling. A high environmental impact can be achieved if the load scheduling algorithm is widely used, resulting in a significant cut of carbon emissions due to reduction of energy consumption and more evenly distributed load across time. Finally, the principles we proposed are tested in a normal residential test house in Liverpool. For test reason and also further commercialisation, a user-friendly web based APP has been developed to become a potential commercial product of BE Thinking Ltd (previously branded Inteb Sustainability Ltd.). The main feature functions include: 1) machine learning based users' preference prediction and environmental parameter determination. 2) easy-to-use energy consumption monitoring and analysis. 3) Optimisation algorithm based automatic energy usage suggestion service.

The effectiveness of our integrated and intelligent IT solution has been analysed by computer simulation and validated through a test house. The feedback from the users has shown the advances of our solution's special features over the existing products on the market, including considering users' preferences, machine learning and intelligent energy management advice etc.

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Chapter 1

Introduction

1.1 Project Background

The research project is funded by the Centre of Global Eco-Innovation (CGE) and Inteb Sustainability. Inteb provides advices for UK buildings' occupiers and investment portfolios on ways to improve energy efficiency, reduce carbon emissions and stay compliant. The CGE is funded by the European Regional Development Fund (ERDF) with the aim "to deliver new products and services which can demonstrate a measurable, environmental benefit, economic value and export potential."

The UK government has launched an initiative to deploy smart meters across the country by 2020, to help consumers manage their energy use, save money and reduce CO_2 emissions with the real-time information on their energy consumption. To fully explore the benefits of smart meters, Inteb is looking for an easy-to-use and low-cost web/App based IT solution for monitoring and controlling the remote/on-site usage of the energy and water in domestic/commercial buildings, including multi-tenants properties, aiming to reduce the energy and water consumption and increase water recyclability.

With the experience of Inteb on building energy management, this project aims to firstly model the house thermal dynamics, secondly design a system to optimise the total energy usage in the buildings considering cost and users' comfort level. Finally to prove the effectiveness on realistic environment.

1.1.1 Smart Grid

Many significant challenges including meeting the projected demand for energy, environmental problems, security, reliability and integration of renewable energy have been realised by the electricity supply industry [1]. To overcome these challenges, many new technologies including renewable energy sources, smart metering and advanced energy management schemes have been developed in recent decades.

Conventionally, the electricity feeding can be seen as a broadcast process (*i.e.*, from few-to-many distribution), where all the electricity requirements of a country or region are fulfilled by several power plants generates via a large network of cables and transformers [2]. According to historical usage data and load forecasting models, the utility providers generally over-provision for the demand (considering peak load conditions). Thus if the real-time demand goes above the average, additional power plants (usually with non-renewable sources *e.g.* coal fired plants) are used to compensate the demand. The operation of these additional plants can be wasteful if there is no need for extra generation since electricity has to be consumed immediately as grid energy storage is expensive [3]. Plus, setting up and maintaining the peaker plants is both environmentally unfriendly and expensive. Additionally, with the rapid increase of electricity demand, to match the supply to the peak demand might be difficult or even impossible in the far future.

Under this background, to match the demand to the available supply by using two way communications between the grid and customer premises and providing incentives (*e.g.* through variable pricing) to the end user to reschedule the load during times when the expected demand is lower so as to improve utilization of the available capacity can be a premier target for the construction on the power grid. The information of the communication between the customer premises and the grid can include the metering information from the customer to identify the demand and in return, the pricing signal of the main grid to make the customer adapt their demand into current generation. Due to the fact that the legacy grid is a broadcast grid, this become the most important motivation for a new communication infrastructure and protocols to support the above functionalities [3].

Although the old power grid has been operating well in the past few decades, there is still a need for it to be updated to a much better version. There are mainly two reasons: for aging infrastructure and the new environmental and societal challenges. Many governments and nations have started the Smart Grid project for the future benefit.

Smart Grid is a concept for transforming the electric power grid by using advanced automatic control and communications techniques and other forms of information technology. It integrates innovative tools and technologies from generation, transmission and distribution all the way to consumer appliances and equipment [4]. This concept makes energy generation, distribution and consumption more effectively and efficiently by the integration of energy infrastructure, processes devices, information and markets into a coordinated and collaborative process.

One of the most important feature of smart grid is to increase the use of renewable energy sources (RES). Renewable energy brings many benefits in terms of economics and sustainability. Therefore, many countries, including the United States, have enforced adoption of renewable energy. For example, California mandates that 33% of total energy will be generated from renewable sources by 2020 [5]. However, there are many challenges when integration renewable energy sources. The biggest thing is scalability and timing problem. Since renewable energy sources are highly dependent on the environmental factors, for example, wind speed and the timing of sunshine, this makes renewable energy generation highly unstable [6]. For the promise of an alternative energy source to be achieved, it must be supplied in the time frames needed and in the volume need. For legacy power grid with no information on neither generation or consumption, the renewable energy generation can only be a small part of the total amount needed.

Another import feature of Smart Grid is demand management, huge savings can be achieved through the process of generating and transmission of energy because of the reduction in number of power plants needed to satisfy the peak demand which only happens in a very small occasion of time. The data shows that in Europe, 5% to 8% of the power plants are only used for 1% of the time [7]. 67 billion euros can be saved for capacity and transmission cost by identification of peak and off-peak demand [7]. McKinsey forcasts that over 130 billion dollars saving can be achieved with a fully deployed smart grid in the US [8]. Apart from the direct savings, many important economical and societal benefits (*e.g.* CO_2

reductions, elimination of regional blackouts and reduced operational cost via automated meter readings) can be also achieved during the process of smart grid update.

Huge amount of investments on smart grid research and development are being made in many different countries. In the US, smart grid is an essential component of President Obama's comprehensive energy plan: the American Recovery and Investment Act includes $11 billion in investment to "jump start the transformation to a bigger, better, smart grid". In the Europe, a more robust system than the US's is presented with highly interconnected, mesh distribution network. A program of large investments in updating the distribution network has been agreed at EU level [9].

1.1.2 Smart Home Infrastructures

The cornerstone of a smart grid is the ability for multiple entities (e.g. intelligent devices, dedicated software, processes, control centre, etc) to interact via a communication infrastructure. It follows that the development of a reliable and pervasive communication infrastructure represents crucial issues in both structure and operation of smart grid communication systems [10, 11]. In this connection, a strategic requirement in supporting this process is the development of a reliable communication infrastructure for establishing robust real-time data transportation through Wide Area Networks (WANs) to the distribution feeder and customer level [12]. Existing electrical utility WANs are based on a hybrid of communication technologies including wired technologies such as fiber optics, power line communication (PLC) systems, copper-wire line, and a variety of wireless technologies (i.e. data communications in cellular networks such as GSM/GPRS/WiMax/WLAN and Cognitive Radio [13]). They are designed to support some monitoring/controlling applications as Supervisory Control and Data Acquisition (SCADA)/Energy Management Systems (EMS), Distribution Management Systems (DMS), Enterprise Resource Planning (ERP) systems, generation plant automation, distribution feeder automation and physical security for facilities in wide range areas with very limited bandwidth and capacity in closed networks.

Many applications such as energy metering on the smart grid, have emerged from a decade of research in wireless sensor networks. However, the lack of an IP-based network architecture precluded sensor networks from interoperating with the Internet, limiting their real-world impact. The IETF chartered the 6LoWPAN and RoLL working groups to specify standards at various layers of the protocol stack with the goal of connecting low-power devices to the Internet. In [14] the authors present the standards proposed by these working groups, and describe how the research community actively participates in this process by influencing their design and providing open source implementations. The new communication infrastructures should evolve toward nearly ubiquitous data transport networks able to handle power delivery applications along with vast amount of new data coming from the smart grid applications. These networks should be scalable, in order to support the present and the future set of functions characterizing the emerging smart grid communication technological platform, and highly pervasive in order to support the deployment of last-mile communications (i.e. from a backbone to the terminal customers locations) [15]. In the rest of this section, we discuss several key factors for smart grid systems including power line communications, distributed energy resources, smart metering, and monitoring and controlling.

With the rapid development on networked devices into home environment, the desire for automatic home energy management has been increased recently. On one side, the users want to maximise their comfort level. However, users may not have the knowledge or time to optimally manage their device execution. On the other side, the landlord wants to minimise the energy bill. However, during most of the time they do not know the real-time energy consumption of the building [16].

A number of research projects and research have developed ubiquitous home network models. Compared to traditional home networks, the in-progress ubiquitous home network collects user activity awareness, as well as physical sensing information in the home environment, to support more smart and well-being home services. It is essential to easily control consumer home network services used in livelihood. Eventually, users will experience the convenience of performing ordinary life styles and increased satisfaction offered by adaptive home services. Context-aware [17] is a kind of intelligent computing activities. For the humans, context-awareness is an essential capability for understanding the implicit information that is associated with the activities that they conduct. For example, context-awareness enables a person to follow an continuing conversation, and context awareness can help to guide the appropriate actions of a student when the student enters a classroom. For the computing systems, however, context awareness is the capability to provide relevant services and information to the users based on their situational conditions (i.e., contexts). Several conditions are required to reap advantages from the ubiquitous home network. For instance, context aggregation [18] should integrate diversified sensing information to perceive the current situation in the surrounding environment. Also, they should be able to control various consumer home devices. Therefore, Context aggregator should be designed distributing various tasks into proper computational units to reduce complexity. The home network systems may become complex, as the number of sensors and devices offered increases. Using a wireless sensor network with actuator functionality, our system can automatically gather physical sensing information and efficiently control various consumer home devices.

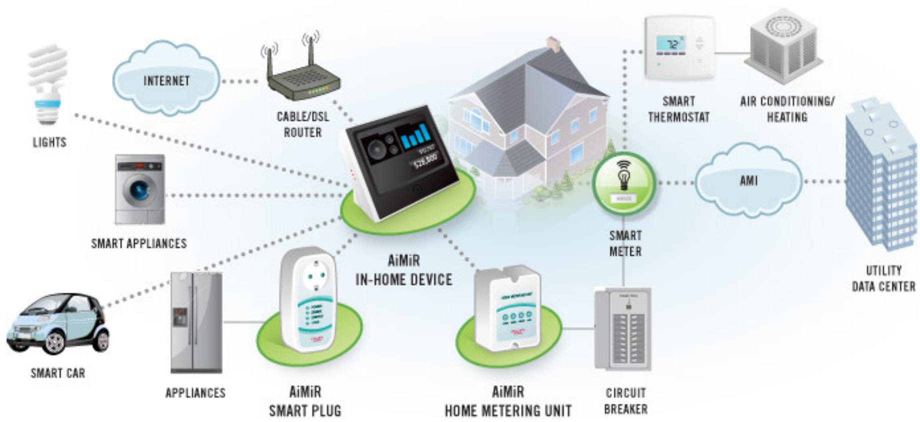

Fig. 1.1 Smart Home Energy Management System [19]

Fig 1.1 shows an overview of a smart home energy management system. The system, being supported by underlying personal area networks and additional wireless communications technologies, can control consumer home devices such as lamps, gas valves, curtains, TVs, and air conditioners. It also interoperates with various mobile devices, such as PDA and mobile phones, using IEEE 802.11/802.3. This Smart Home Energy Management System (SHEMS) based on personal area networks consists of various software components as follows. Sensing Infra: the component gathers sensing data and special event information from the personal area networking infrastructure deployed in home environments[20]. This sensing component provides this information to the decision component. A consensus definition of context is a collection of information that characterizes a person or a computing entity. Within in the smart space environment, the author defines the notion of context as the following: by context, I mean an understanding of a location and its environmental attributes (e.g., temperature, noise level, light intensity), and the people, physical objects, and computing entities that it contains. This understanding necessarily extends to modeling the activities and tasks that are taking place in a location as well as the beliefs, desires, commitments, and intentions of the human and the software agents involved.

Most of the smart home infrastructures and technologies available in the mass market are quite similar. Based on a bi-directional communication method through various communication protocol (Radio Frequency, Zigbee, Wifi etc.), most of the products now have the abilities to be remotely controlled by authorized users and specific usage data can be collected through regulated data feeding process. Any device in the smart home that uses electricity can be put on local network and at users' command. Whether a command is given by voice, remote control, tablet or smartphone, the home reacts. Most applications relate to lighting, home security, home theater and entertainment, and thermostat regulation.

As shown in Fig 1.2, any device in the smart home that uses electricity can be put on local network and at users' command. Whether a command is given by voice, remote control, tablet or smartphone, the home reacts. Most applications relate to lighting, home security, home theater and entertainment, and thermostat regulation.

Evolving technologies in the energy and utilities industry, including smart meters and smart home infrastructures, can provide smart home companies with unprecedented capabilities for forecasting demand, shaping customer usage patterns, preventing outages, optimizing unit commitment and more. At the same time, these advances also generate unprecedented

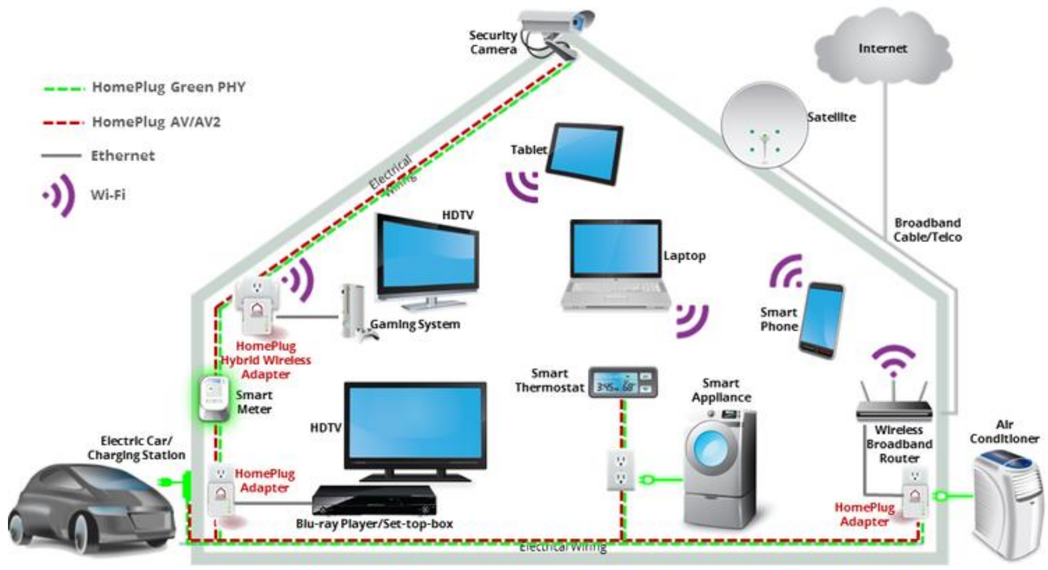

Fig. 1.2 Smart Home Network Diagram [21]

data volume, speed and complexity. To manage and use this information to gain insight, smart home companies must be capable of high-volume data management and advanced analytics designed to transform data into actionable insights. For example, designing effective demand response programs requires that utilities execute advanced analytics across a combination of data about customers, consumption, physical grid dynamic behavior, generation capacity, energy commodity markets and weather. In our project, we focus specifically on the ability for smart home companies to transform collected data and external data (*e.g.* weather forecast information by third party) into actionable insights. This mainly includes the ability to further process the data in the following aspects.

- An event based algorithm which takes all kinds of events data into consideration and reacts with certain instructions. For example, if we detect water leakage, turn off water supply and report to the house owner.

- Statistical algorithm based data processing method for data analytics. More information can be found if the data are treated properly. For example, applying Artificial Neural Network (ANN) can detect potential impacts on house heating system.

- Data gathered from smart meters can provide better understanding of customer segmentation, behavior and how pricing influences usage—if companies have the capability to use that data. For example, time-of-use pricing encourages cost-savvy retail customers to run their washing machines, dryers and dishwashers at off-peak times. These customers not only save money but also require less generation capacity from their energy providers, which means lower capital outlay for new generation and overall greater operational efficiency for utilities.

1.1.3 Building Thermal Model

The changing importance of building physics in design, along with improved technological capabilities, has led to an evolution in the attempts to model the complex dynamics of the energy flows in buildings. Ultimately, the need for accurate modelling and simulation techniques is to aid design decisions. Early modelling attempts would generally be "steady-state" models, whereby a building could be broken down into an array of points or "nodes", with energy flows between different nodes, as shown in Figure 1.3. Such a system of nodes can be thought of as an electrical network: each node is at a different temperature (analogous to voltage), and there are heat flows between nodes (analogous to current), with the rate of transfer dependent on the thermal resistance (analogous to electrical resistance).

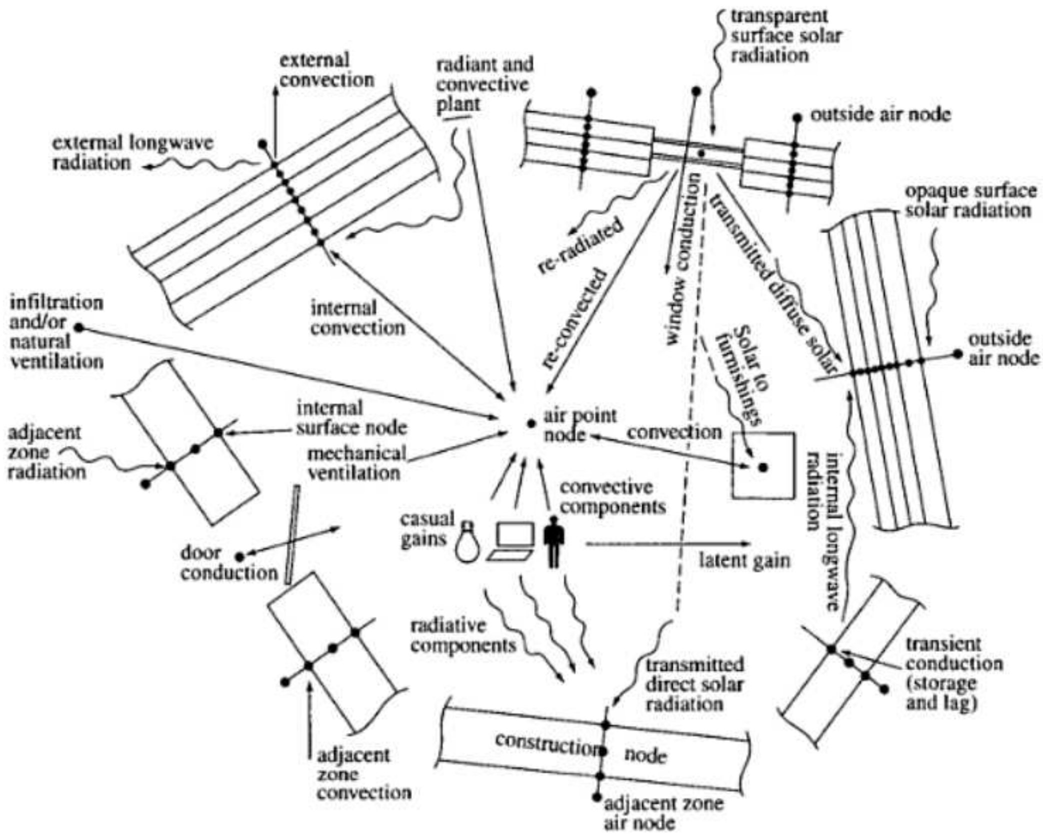

Fig. 1.3 Energy Flow in Buildings [21]

The main problem with such a steady-state model is that the environment clearly varies with time; weather variations, both daily and annually, result in significantly varying external temperatures, wind speeds, and incident solar radiation. Not only are there weather variations, but the activity within the building also varies, and thus casual gains are constantly changing. Meanwhile, the effect of thermal mass in the building allows energy to be stored and released, adding yet another temporal variation.

As computing power increased, dynamic models of energy flows in buildings began to appear. These dynamic models are based on the equations governing energy and mass transfer, and avoid many of the assumptions and limitations of previous simplified models.

For example, dynamic models can capture the time-dependency of energy flows, such as climactic conditions, thermal mass, and internal gains. The added complexity of dynamic models comes as a cost though: they are more time-intensive than steady-state models, both in terms of the time needed to construct the model and also the time needed to run the simulations, whilst they also require a greater level of details in terms of inputs to the model.

1.1.4 Smart Grid Demand Side Management

DEMAND-SIDE management (DSM) has been developed since early 1980s to balance the time-varying demand load of consumers and maximum power generation capacity in the power system. In DSM, the pricing mechanisms and direct control strategies are employed by the energy suppliers to affect consumers' consumption behaviors and reshape the total load [22–24]. The time-of-use pricing strategy sets different prices during the day to encourage consumers to shift their demand to off-peak hours [25–27]. Similar to the time-of-use pricing, the critical peak pricing applies a prespecified high price during the designated critical peak periods [28, 29]. The real-time pricing adopts the time-varying price according to the wholesale price of electricity and the cost of power generation to enable consumers to adjust their demand in response to supply [30–34].

The demand side management is the form of programs which are implemented by the utility companies to control the energy consumption at the customer side [35, 36]. DSM aims to manage the load to satisfy certain intents by monitoring the demand side activity (smart metering) and or load scheduling with collected data. The DSM approaches can offer more efficient consumption for without the demand for extra generation and transmission infrastructures [37]. A decentralized DSM mechanism to deferment of home loads is based on grid prices and utility companies offer the incentive to use the devices optimally which in turn reduces the heating. The heuristic based evolutionary algorithm is used for day-ahead load shifting to reduce the peak demand and reshape demand curve [38]. The DSM facilitates the consumption of locally generated energy immediately whenever it is available for local loads [39]. The main advantage of DSM's, is that of its less expensive nature to intelligently influence a load [40].

Except following the pricing mechanisms made by the supplier, consumers' consumption goals can be also achieved by applying the consumer side residential load scheduling algorithm [33]. Metrics are normally used to demonstrate the consumption cost and consumption payoffs for evaluation of consumer's consumption behavior. There are many researches about load scheduling algorithms to optimize consumption cost of users. Conservative consumption modes are developed with the aid of these programs. Additionally, these algorithms did not simply minimize the usage cost but also took users' comfort level into consideration. Guided by this metric, a number of the existing load scheduling methods are based on this concept of payoff functions and design algorithms to maximize the payoff in the scheduling optimization. These programs enable the consumer to pursue the best consumption benefit within the consumption limit.

As shown in figure 1.4, to achieve better management of electricity consumption, the utility companies introduced real-time pricing schema to lead the consumer side self-driven energy usage habits. Users then attempt to reduce their energy cost with the information provided by their local energy provider.

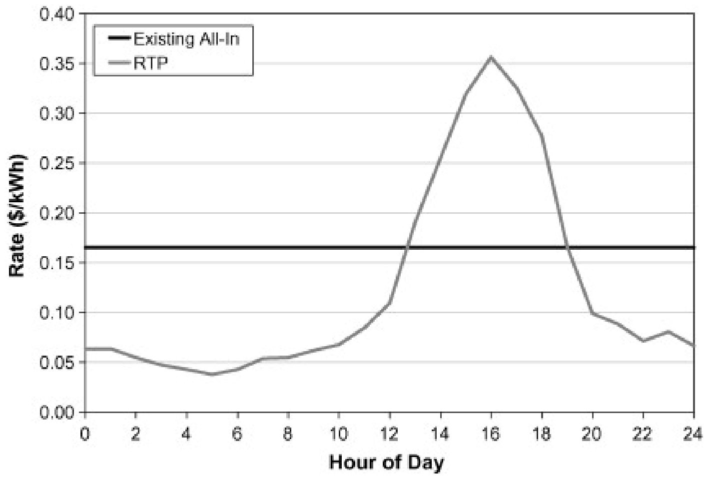

Fig. 1.4 Real Time Pricing

1.1.5 Load Scheduling

Due to the fact that the consumers are neither economists nor experienced grid operators, it is impossible to request them to create an optimal household load schedule to save energy, reduce cost, and help grid operation (e.g., by reducing the contribution of the consumer to the peak load). To solve this problem, automatic load scheduling methods should be provided, which can collect status and power consumption demand from home appliances and schedule them in an energy- and cost-efficient way by simultaneously considering comfort as well. Pedrasa *et al*. described algorithmic enhancements to a decision-support tool to help consumers optimize their acquisition of electrical energy services in [41]. The decision-support tool can optimize energy service provision by enabling end users to first assign values to desired energy services and then schedule their available distributed energy resources (DER) to maximize net benefits. A solar photovoltaic (PV) system was considered as an example of renewable energy sources in [42] but the solar insolation was roughly described as sunny or cloudy in days, which is not accurate enough for scheduling household load in hours. Du et al. presented an appliance commitment algorithm to schedule thermostatically controlled household loads in order to meet an optimization objective such as minimum payment or maximum comfort in [43]. Both price and consumption forecasts and users' comfort settings were considered in the algorithm but the utilization of renewable energy sources was missing, which will play an important role in the future residential energy supply system [44].

Several studies have been conducted on residential home load scheduling. Reference [45] studies a typical microgrid for buildings and energy savings provided by facilitating buildings with micro-grid technology. They have assumed a CHP unit and an HVAC system to meet thermal demand which is considered as a total profile of required thermal energy for 24 hours of a day in the building. Reference [46] studies implementing demand response (DR) with micro-CHP systems by utilizing flexible thermal demands. It shows that, by implementing DR, operation cost would be reduced in comparison to heat-led control of a micro-CHP unit; however, flexible electrical demand is not considered. In most of the studies, thermal load is normally considered as a profile which shows building thermal energy required at each time-step without segregating it into its constituent components[47, 48]. Therefore, it is difficult to understand how to make this thermal demand profile coordinate with electrical demand profile. In this paper, the building's required thermal energy is analyzed more precisely in the form of desired hot water and building temperature. This provides an opportunity to study the effect of flexible thermal loads in operation of micro-CHP based micro-grids. In this framework, acceptable intervals around the desired temperatures for the building and the water storage are assumed considering consumers' comfort level. This flexible thermal load would help the coordination of the micro-CHP's electrical and thermal output power. Then, optimal temperature for economic operation of the micro-CHP is determined at each time-step while the dependency between time intervals is taken into account. According to the technology action plan for smart grids announced in Copenhagen in December 2009 by the Major Economies Forum (MEF), "active demand response" and "integration with smart home" are considered as the first items on the smart grids technology fact sheet [49]. Smart meters that have bidirectional communication capacity are central components for the operation of smart consumers. A smart meter is an advanced meter that can be used to identify and measure power consumption electronically and can communicate this information to another device [50]. Some of the smart meters are equipped with a display for sending data on the amount of power consumed or the corresponding cost to the customers. In-home-display (IHD) is an additional display for sending information to customers. One of the types of smart meters is the power strip type smart meter (SMPT); these meters have one or more ports with current and/or voltage sensors for power monitoring and a relay for power control [51, 52].

As mentioned before, electrical demand should also be flexible to be coordinated with thermal demand, allowing to implement DR programs. In a microgrid equipped with smart meters, numerous data would be available which can be processed for several goals. Reference [53] describes a method of appliances location determination from the multi-hop tree structure of SMPTs. Reference [54] presents a method of extraction of user's activities from electric power consumption data which is provided by SMPTs. In this study, the data is provided by SMPTs showing the energy consumption and operation time of each electrical appliance in a house. Besides specifying each appliance's share from total electrical demand, appliances are also categorized into shiftable and nonshiftable loads. Then, an optimization module decides to employ load shifting in such a way that electrical demand is coordinated with thermal demand while considering the main grid time-of-use (TOU) price tariffs. Electrical power storages such as batteries help in implementing DR as well. They can charge during hours in which the main grid electricity price is low and discharge during peak price hours helping to reduce micro-grid operation cost.

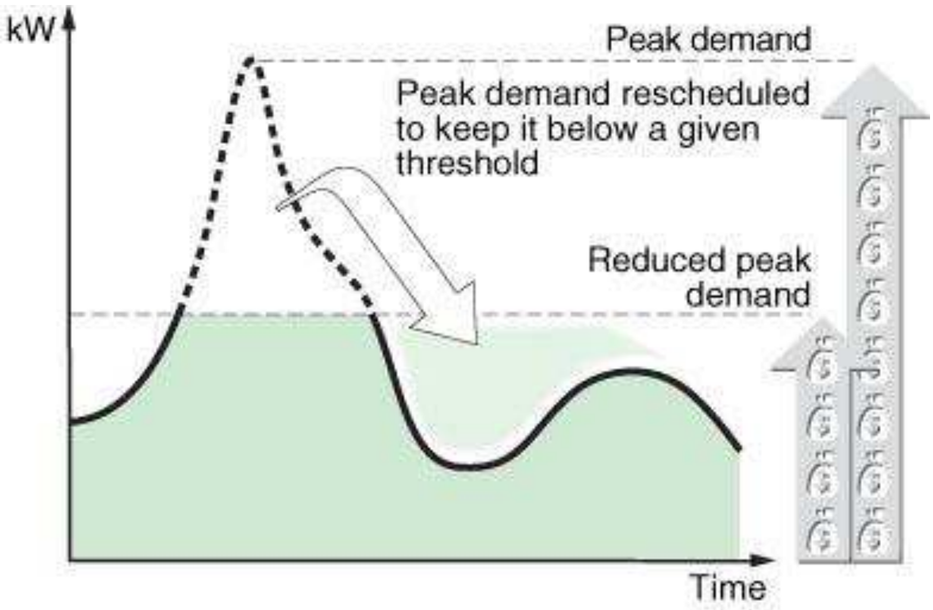

Fig. 1.5 Basic Model of Load Scheduling [55]

Figure 1.5 shows a common scenario of load scheduling. To reduce the peak load we cut some of the controllable loads of peak time to off-peak time to execute. By this mean, not only the user benefits from the energy bill, also the whole community will achieve higher energy efficiency because of the flattened load curve.

1.2 Project Objectives

- Model the building thermal dynamics and temperature change into a discrete time model.
- Design a system to schedule the building heating usage by predicting the thermal change to achieve desired comfort level (measured mainly by room temperature) of users.
- Design a system to schedule all the electricity devices in the buildings to achieve low cost under real-time pricing policy and users' requirements.
- Test the effectiveness of the system under realistic environments.

1.3 Motivation

- Previous methods mostly estimate the parameters in house thermal model. The models are relatively complicated and the estimation process takes long time to finish. Therefore, it is not quite suitable for house energy management since it has a high requirement on convergence speed.
- Previous methods require professional operation for the users to determine the parameters. For normal residential users, they do not have such skills. So an automatic setting methods is needed.

- Previous methods doesn't consider the potential impact of multiple heating resources despite the fact that neighbouring heating may have an impact on the room temperature change.

- Previous load scheduling algorithms minimizes the cost level but did not look into users' comfort level. With precise prediction on house thermal model. The author's method can offer a cost-effective solution to fit users' comfort requirements.

- Our load scheduling method can be flexible for users, so users can determine whether they want more comfort or they need less cost on their energy usage.

Chapter 2

Literature Review

2.1 Introduction

Smart grid implementation and smart home automation have been a topic of interest in the research world for the last few decades. The main researches focus on smart grid demand side management, load scheduling techniques, smart metering and smart appliance control and micro-grid controlling. The purpose of this study is to explore some of the different approaches other researches do. The scopes of literatures we investigated are mainly in the session of residential load scheduling, residential house thermal modelling, artificial neuron network and smart grid techniques. Most of the sources showed the realism and good performance of smart grid technologies and smart home techniques. Some of them showed both simulation and experimental results in real environment, which makes it more convincing for future implementation. We believe that smart grid and smart home is the future trend of core technology in terms of electricity generation and consumption.

2.2 Matchstick Thermal Model Learning

C.Ellis, M.Hazas and J.Scott [56] presented a room-to-room thermal model used to accurately predict temperatures in residential buildings. There are two general types of approach for modelling a building's internal thermal interactions: process-driven and data-driven. These are also known as the forward system identification and inverse system identification [57].

Matchstick, which is their proposed model, takes room-to-room interactions, thermal mass delays, and outside temperature into consideration. The approach "matchstick" achieves better representation of the thermal mass presented in each room's heating element and structures by applying a non-linear transformation to the gas usage.

The model acts as glue between the heating scheduler (for example, a programmable thermostat or an occupancy predictor which dictates setpoint and setback times) and the controller of a heating system. Upon the model is trained on historical usage data, it provides the ability to tell what is very likely to happen in the future based on current sensor measurements and proposed heating schedule. With the information provided by trained model, heating controller then schedule the heating program to satisfy the intent of the program, which can be either saving gas/electricity and/or increase comfort level. A high-level diagram in figure 2.1 shows how their model "Matchstick" works.

Their proposed problem is very similar to the one we proposed in this thesis. The goal is to achieve better performance of house heating control system based on the prediction. They counted current temperature of each room, heating output to each room and the outside temperature into consideration. A stunning point is that they used a recursive non-linear transform function to take the raw gas usage for a heating system and the current valve state

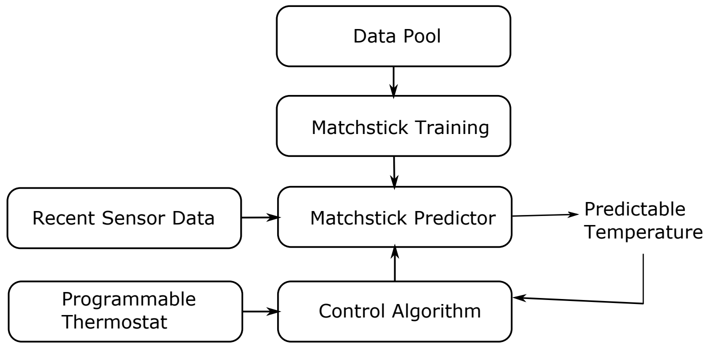

Fig. 2.1 Matchstick Working Diagram

for the radiator (which in their case is either fully open or fully closed). For heating loss function, they used ETPs [58] to calculate the value. Thus the system model describes how the last known temperature and thermal output affects a room, together with neighboring room thermal flows, and environmental measurements.

However, their method still uses a thermal loss model, which cannot be universally accurate. In addition, they did not count in the human behavior of the house which can have significant impact on indoor temperature change.

2.3 Neuron Network Electricity Consumption Prediction

A.Songpu *et al.* [59] Proposed a neural network based historical domestical load data learning procedure to predict active and reactive power consumption of a house. They used data collected from a Southern Norwegian house (active and reactive consumption and time information) as inputs. Also, before using the data for training purpose, they corrected the missing and inaccurate data then use the data for testing the model.

The overall structure of the model is illustrated in Fig 2.2. To establish a prediction model using the hourly power usage data, the input of this model is taken combination of time and power (active and reactive) usage data. In this work, through trajectories, the combinations of "month, hour, day of week, workday/holiday, last three hour's power consumption, yesterday the same hour's power consumption, and the average power consumption of last 24 hours" are taken as input data. By taking these 9 components as inputs, the highest average regression value R could be achieved by comparing with other input combinations. Regression value R is introduced here to evaluate and compare the prediction results. R measures the correlation between the power consumption prediction result and the practical / actual power usage. R=1 means that a very close relationship exists between the prediction results and targets. In contrast, $R = 0$ means random relationship.

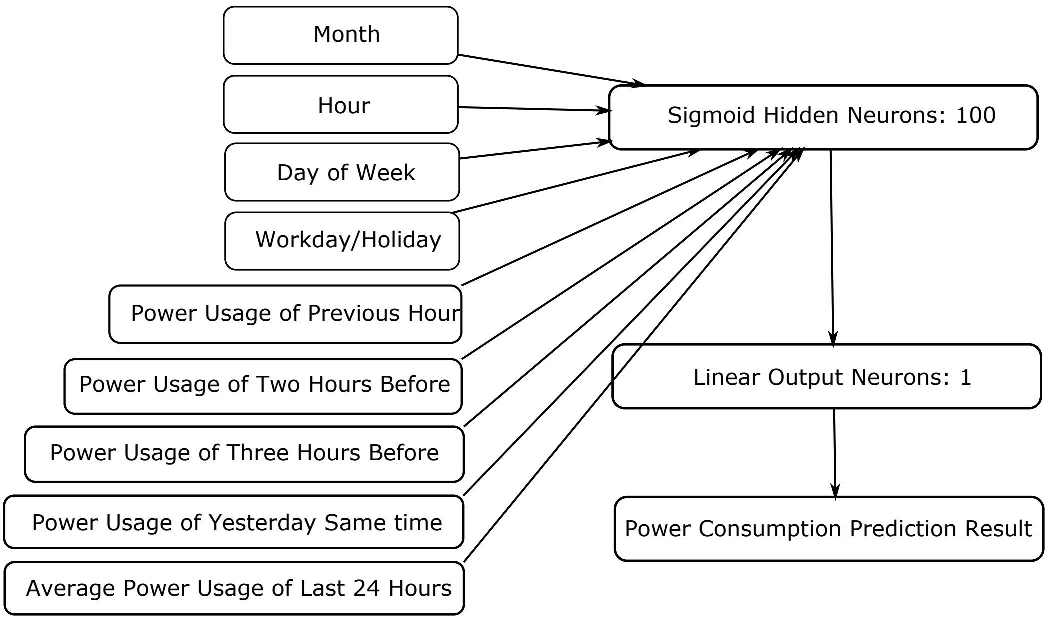

Fig. 2.2 Neural Network Diagram

Figure 2.2 shows the overall structure of the proposed model. The input of the model takes combination of time and power (active and reactive) usage data to setup a prediction model by using the hourly power usage data. They took month, hour, day of week, workday/weekends/holidays, the consumption of last three hours, the power consumption of the same hour yesterday and the average power consumption during last 24 hours into count. Taking those components as inputs, maximum average regression can be achieved by comparing with other input combinations. They introduced regression value R to evaluate and compare the prediction results. Generally speaking, this value shows how correct is the results between the actual power usage and predicted usage.

Their proposed method used neural network which has a similar architecture of ours. However, firstly, the input parameters are quite limited and non-adjustable which may be accurate for certain house scenario, but can be not adaptive to other houses. Also, the model didn't take the impact of neighboring heating input into consideration. Which can lead to in-accurate prediction.

M. Safdar *et al*. [60] proposed a method to evaluate the potential of demand response in reducing the peak load demands as well as electricity bills to the domestic electricity users.

They used MATLAB Simulink to model the domestic appliances and energy management controller to control these devices which have been categorized into either controllable or controllable. Based on the outcome of the optimization algorithms, energy management controller decides the switch status of the controllable appliances to achieve certain design intents.

They used Mixed Integer Linear Programming (MILP) algorithm to solve the proposed problem. Different constraints are considered during the optimization problem including user comfort level, needs for regular life operation and the priorities of them in many different cases.

n their research, they considered RTP (real-time pricing) and FTP (fixed-time pricing). RTP holds the day-ahead forecasted price of electricity and FTP represents a constant tariff.

They listed several domestic loads in figure 2.3:

Sr. No.	Description	Load (Watt)	Operation	Type
1 (A)	Dish Washer	1500	60 Min.	Controllable
2 (B)	Washing Machine	1000	55 Min.	Controllable
3 (C)	Refrigerator	1200	Continuous	Uncontrollable
4 (D)	Clothes Dryer	800	45 Min.	Partial Controllable
5 (E)	Air Conditioner (AC)	2000	As per need	Uncontrollable
6 (F)	Television (TV)	200	As per need	Uncontrollable
7 (G)	Deep Freezer	1000	Continuous	Uncontrollable
8 (H)	Electric Iron	1100	30 Min.	Controllable
9 (I)	Water Heater	500	As per need	Uncontrollable

Fig. 2.3 List of Domestic Loads

The aim of their optimization procedure is to produce a set of optimized schedules of domestic appliances to achieve the minimum electricity cost. Both the formulation of objective function and the criteria which are the constraints are taken into consideration in the optimization algorithm to validate it. They used the method proposed in [61] for MILP optimization technique to calculate the minimum electricity cost. There are certain constraints which are device specific and some are user specific. User can define some of the constraints according to their needs. An example of device specific constraint is that clothes dryer can only be operated after washing machine ends its operation.

They used mixed integer linear programming for residential load scheduling, which is quite similar to our exhaustive search method. And the problem formulation is quite similar. However, they did not consider the thermal comfort level of the user. Also, the scheduling problem did not consider the renewable energy generation and consumption.

2.4 Load Scheduling Algorithms

Thanh Dang and K. Ringland [62] proposed an optimal load scheduling algorithm to minimize energy cost for residential homes in smart grids. The algorithm is designed for smart grids with renewable energy sources, energy storage, and two-way communication and energy dispatch. Each appliance in a home has jobs that can be deferred but have deadlines. The algorithm takes into account day-ahead pricing with inclining block rates from energy retailers, local energy generation information from renewable sources, and future jobs to make decisions on when to buy or sell energy while still accomplishing the jobs before their deadlines. The algorithm achieves its optimality by formulating a linear optimization problem that can be solved efficiently. They claim their method can reduce energy cost by 20% and peak energy consumption by 100% compared to other approaches. However, the comfort level of users are only measured with the delay of execution time of devices but no heating systems are considered.

D. Brunelli and L. Tamburini [63] proposed a method to solve complex residential load scheduling problems considering users' customization and configuration of residential parameters such as residential renewable resources and Hybrid Electrical Storage System (HESS). The scheduler takes into consideration different classes of residential appliances and price-control to minimise the cost of the energy and maintenance. This method gives a good example of how to manage renewable energy storage and considered users' requirements by assigning priority, along with presence of alternative energy sources. However, they didn't consider the heating condition as users' comfort level.

B. Chai, Z. Yang and J. Chen [64] considered the power consumption expense, the robustness of schedule subject to uncertain electricity price and the satisfaction of customers. They proposed a convex optimisation problem which simultaneously optimises the three indices. Also, to fully characterize the operation states of appliances, both binary and continuous variables are used, which results in a hybrid optimisation problem. Both peak-to-average ratio of power load and variation of power load are reduced. The comfort level of customers are measured using the total shifted time of appliances, which didn't take users' thermal comfort into consideration.

D. Brunelli and L. Tamburini [65] mentioned that recent studies have shown that the lack of knowledge among users about how to respond to time-varying prices as well as the lack of effective building automation systems are two major barriers for fully utilizing the potential benefits of real-time pricing tariffs. They proposed an optimal and automatic residential energy consumption scheduling framework which attempts to achieve a desired trade-off between minimizing the electricity payment and minimizing the waiting time for operation of each appliance in household in presence of a RTP tariff combined with inclining block rates. The model they proposed needs very few effort from users and uses linear programming algorithm for simplicity. Their work gives a fundamental residential house model however the comfort level they used is still related to the appliances' shift time where no heating conditions are considered.

G. Koutitas [66] investigates load control and demand response in a smart grid environment where a bidirectional communication link between the operator and the smart flexible devices supports command and data flow. Two control schemes are investigated that can provide energy management, taking into account user's comfort, via binary on-off policies of the smart flexible devices. A dynamic control algorithm is introduced that considers real time network characteristics and initiates command flow when critical parameters exceed predefined thresholds. To sustain fairness in the system, priority based and round robin scheduling algorithms are proposed. A continuous control algorithm is also explored to define the higher bounds of energy savings. To quantify the discomfort of users that participate in this type of services, a heuristic consumer utility metric is proposed and measurements with a flexible device (air conditioning unit) are performed to model empirically possible time intervals of the control scheme. Reciprocal fair energy management schemes are investigated being both operator and user centric. It is shown that great energy and cost savings can be achieved providing the required degrees of freedom to the smart grid to self-adapt during peak hours.

K. M. Tsui and S. C. Chan [67] proposed an $L1$ regularization technique to deal with schedule-based appliances (SAs), for which the on/off statuses are governed by binary decision variables. the problem has been reformulated as a convex programming (CP) demand response optimisation framework for the automatic load management of various household appliances in a smart home. Its major advantage is that the overall DR optimization problem remains to be convex and solution can be found efficiently. This paper gives a good solution for load scheduling problem but still users' comfort level is not considered.

2.5 Heating Dynamics Prediction

H. Madsen and J. Holst [68] described a method for estimation of continuous-time models for the heat dynamics of buildings based on discrete-time building performance data. The parameters in the continuous-time model are estimated by the maximum likelihood method where a Kalman filter is used in calculating the likelihood function. The modeling procedure is illustrated by using measurements from an experiment where the heat input from electrical heaters is controlled by a pseudo-random binary signal. This paper gives a good deterministic linear state space model in continuous time.

In their research they indicated a thermal dynamics model where the temperature change is a linear model of different input signals (outdoor air temperature, solar radiation, heat supply, etc.) entering the system.

The elements of the model they proposed is also considered in our solution. However, the method they proposed to estimate the environmental parameters either take a long time to train or need the users to have the accurate information on the building structure and materials. The residential house users is not capable to do both.

S. Mallikarjun [69] presents a procedure for constructing building thermal model using experiments, simple sensor and least-absolute shrinkage and selection operator (LASSO). The thermal model so obtained is simple and can be used to construct model based controllers. Further, the methods leads to a linear model as against the non-linear thermal building models making it easier to design model based controllers. The building model is illustrated on a heating, ventilation and air-conditioning (HVAC) test-bed in a laboratory. Their results show that the LASSO based captures the non-linear disturbances and improves the model accuracy. The obtained results are compared with the actual measurements and least-squares to illustrate the accuracy. This paper comes up with a simplified version of building thermal model which we used as a major reference in our project.

Chapter 3

House Thermal Model and Prediction

3.1 Introduction

The building thermal model describes the temperature dynamics of the buildings using Newtons law of cooling [69]. The indoor temperature varies due to a lot of factors mainly including outside temperature change and heating conditions. Also human activities (*e.g.* opening and closing the door, doing indoor exercise) can affect the temperature curve to some extent. How to fit these components into a reasonable mathematical model can be a real question here. In this chapter, a mathematical model is proposed for indoor thermal dynamics and a method to map the impact factors of different environmental variables. Then Artificial Neural Network is used to predict the indoor temperature change of residential house.

Among all these factors, according to past observations, proper house heating operation and human behaviors (e.g. opening and closing door) can have biggest impact on the indoor temperature change. Even though other factors (e.g. house material and size) do matter, much smaller impacts on house thermal model are reflected when these factors alter. In another word, all these impacts are based on "experience" of human and are extremely non-scientific. With the rapid development of smart home infrastructures, more and more houses are now capable of picking up their own heating operation data, which mostly includes the heating scheduling time, actual heating output and the room temperature change. In addition, many third party organizations are now providing local outside temperature as a service. With all information collected and received, "experience" can be generated by machine with proper learning process. Among all the machine learning algorithms, Artificial Neural Network (ANN) has its advantage over other statistical methods including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. In smart home thermal model training, the model is always non-linear and also there are many uncertain impact factors. For example, heating up one room will affect its next room's temperature. Meanwhile Fuzzy is quite good in handling uncertainties and can interpret relationship between input/output by producing rules. During our experiment and real environment testing, ANN combined with Fuzzy theory shows good results in smart home thermal modeling and prediction. In this project, we focus mainly on the houses based in UK and EU where only heating is available and without cooling system.

Fig 3.1 shows the learning circle of smart home thermal model. Collected data and received data are fed into the ANN training model, followed by standard ANN regression

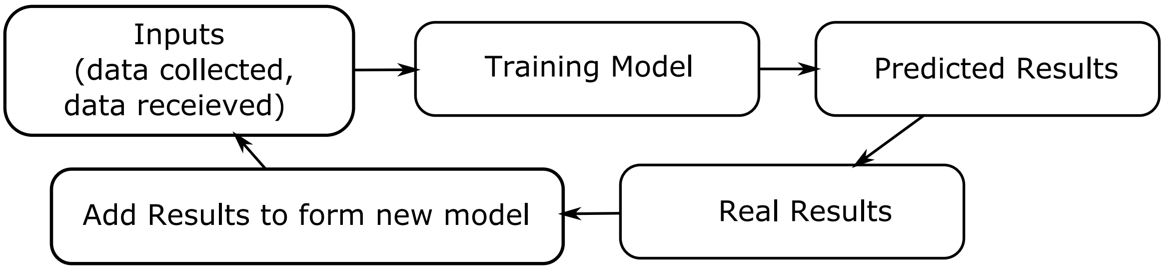

Fig. 3.1 Building Temperature Learning Circle

methods. Then the trained model is then applied to new incoming data to get predictions. These predicted values are then compared with measured data for further training. However, this model should not be running all the time since in reality, it consumes too many resources (power, memory etc). This model ends until certain threshold is satisfied, i.e., prediction error looks generally OK for a short period of time. It is worth to mention that this model will be continuously valid if environmental factor keeps the same (e.g. heating thermostat keeps the same out efficiency or house layout keeps the same.)

3.2 House Thermal Model

3.2.1 Typical Temperature Flow

Figure3.2 shows a typical residential house temperature flow. The temperature stays mostly steady around an average level which is 20 °C. This value normally is associated with outside environmental temperature and weather condition. The red stepped line shows the output of the radiator valve (TRV) in this room. From the graph, we can see that when the output of TRV goes up, which means the room is being heated, the room temperature increases in an observable way. Otherwise, the temperature changes slowly due to other potential influences.

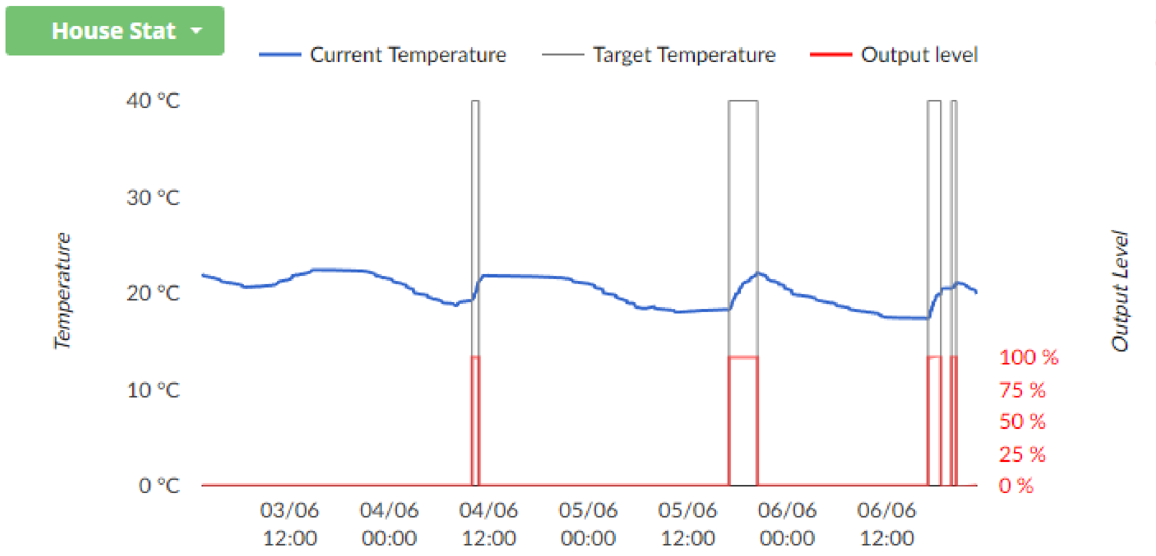

Fig. 3.2 A Typical Residential House Temperature Flow

Typically a residential HVAC system can be referred as either traditional gas/electricity central boiler with distributed radiators in different rooms or individual electricity radiators. There are normally few operation levels which can be adjusted by users to manage the heating level of the room. Changing on/off time of HVAC can be modeled as pulse-width modulation (PWM) that obtains continuous signals using on/off actuation and is suitable for on-off type actuators like the single speed compressor. Hence, we are motivated to use PWM controller for our HVAC systems in these laboratories, and it varies its power output based on the duty cycle, given by $\delta = \frac{P_{on}}{P_{total}}$, where P_{on} is the period of continuous output, and P_{total} is the total time-period. The control input from PWM is

$$u(t) = u(m)\delta \mathrm{sgn}(\delta) \tag{3.1}$$

where m is the input value and $u(m)$ is the maximum value of the applied input and $\mathrm{sgn}(\delta)$ indicates the signal direction. Therefore, if its cooling, the signal will be negative. As the control input obtained form PWM is nonlinear, the building model can be simplified by discretization, and then linearizing the system as in [70]. Then the thermal model of HVAC system can be expressed as:

$$x(k+1) = ax(k) - bu(k) + cw(k) + dv(k) + \varepsilon \tag{3.2}$$

where $x(k)$ is the temperature of the building, $u(k)$ is the duty cycle of the PWM input, $w(k)$ is the heating due to climate change, $v(k)$ is the heating due to human activities in the building and ε is the uncertainty of temperature change. Many influence factors can have impact on this value (*e.g.* unexpected heating resource which has not been taken into account). Parameters a,b,c,d,ε are computed based on the historical data collected from the sensors and meters in the building.

3.2.2 Multiple Heating Resources

When developing strategies to minimise energy consumption within buildings it is crucial to understand the dynamics of energy generation and loss. As mentioned in previous section, there are many impact factors which affect a particular house thermal model. And it doesn't have to be linear.

In practice there will be multiple heating resources in the house affecting one area of temperature. For example, the radiator next door may have an effect on the temperature of this room due to the nature of heating flow and depends on the house structure. In this project, a blind heating resource detection model is proposed.

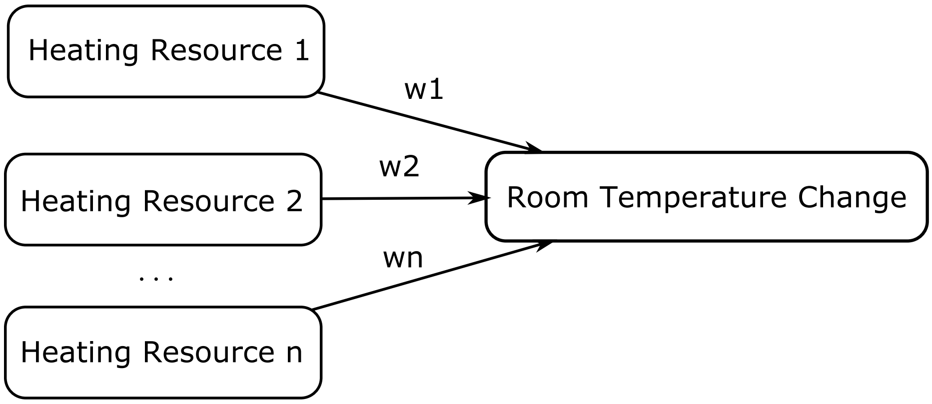

Fig. 3.3 Multiple Heating Inputs

Figure3.3 shows the input model with multiple heating resources. In this model, we take all possible heating resources into the input layer and the weight of each input indicates the impact level of each resource. Within this model, the heating parameter $u(k)$ becomes a vector $U(k)$, is contained of n different radiator outputs of the house. Mathematically written as $(u1(k)+u2(k)+...+un(k))$. The impact parameter $b(k)$ becomes $B(k)$.

3.3 Neural Network Learning

3.3.1 Artificial Neural Network

The idea of Artificial Neural Netoworks (ANNs) is based on the belief that working of human brain by making the right connections, can be imitated using silicon and wires as living neurons and dendrites.

Neurons are nerve cells which has the number of over 100 billion and organize the human brain. Axons are used to connect them with thousands of other cells. Stimuli from external environment or inputs from sensory organs are accepted by dendrites. These inputs create electric impulses, which quickly travel through the neural network. A neuron can then send the message to other neuron to handle the issue or does not send it forward.

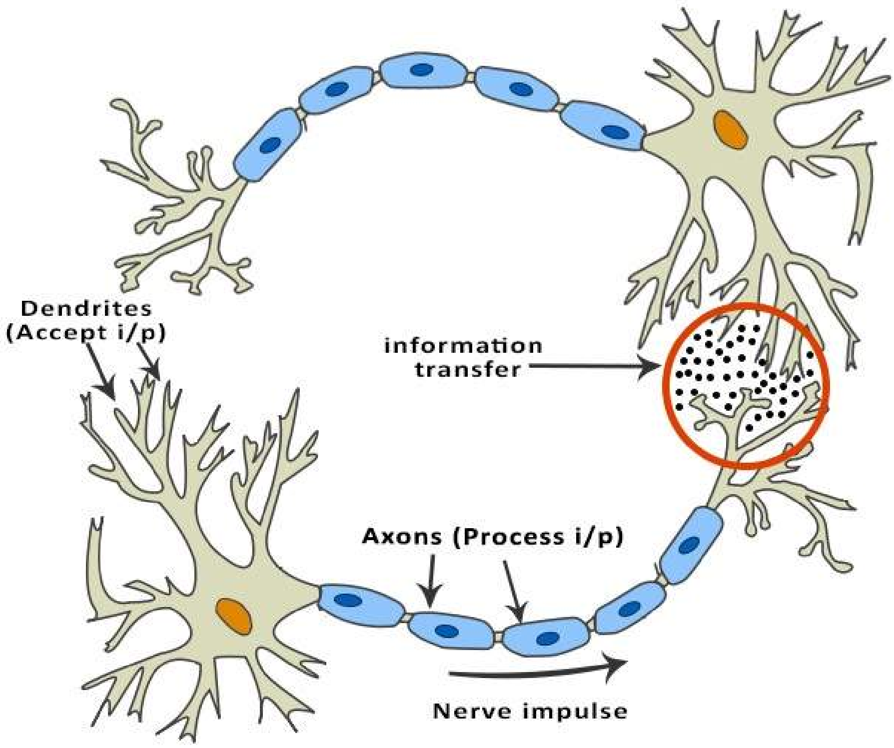

Fig. 3.4 neurons and dendrites [71]

ANNs are made out of various nodes, which impersonate natural neurons of human mind. Links exist among the neurons and enable the communication between each two of them. Input data can be taken by the nodes and simple operations are performed on them. The result of these operations is passed to other neurons. Other neurons receive message based on the result of these operations. The output at each node is called its activation or node value.

Each link is associated with weight. Adjusting the weight values makes ANNs able to learn for certain purpose.

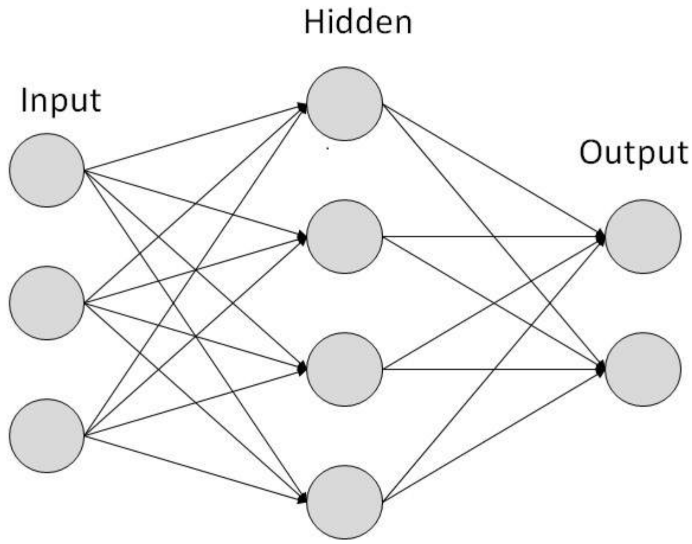

Fig. 3.5 Artificial Neuron Network [72]

There are two Artificial Neural Network topologies: FeedForward and Feedback.

Feedforward ANN

Only one direction is enabled for information flow in this mode. No feedbacks are given when one unit transfers information to other unit. This mode has been widely used in pattern recognition and classification which have fixed number of inputs and outputs.

Feedback ANN

Figure 3.7 shows the feedback ANN. In this kind of model, feedback loops are allowed which are used in content addressable memories.

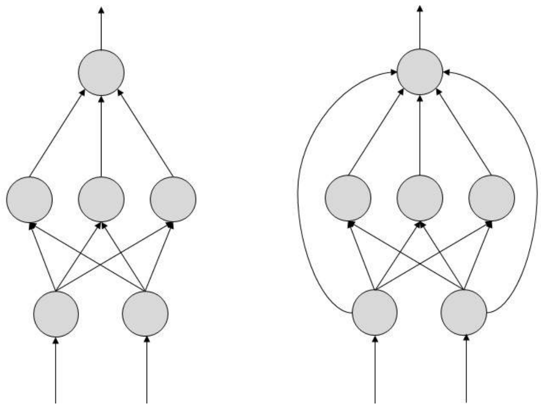

Fig. 3.6 Feedforward ANN [73]

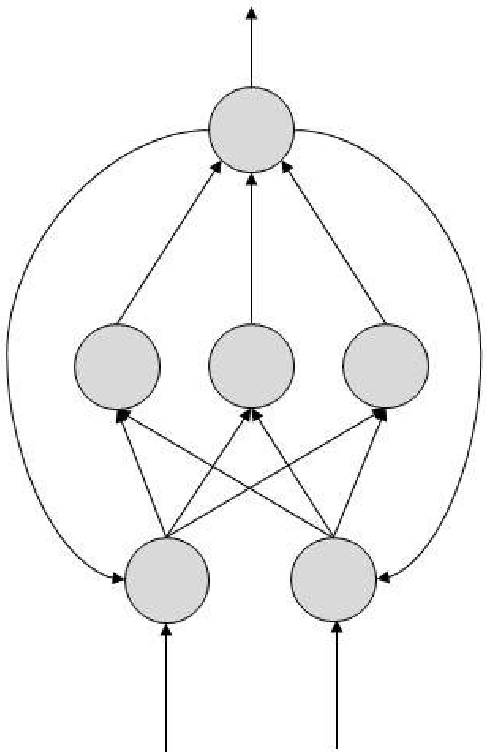

Fig. 3.7 Feedback ANN [73]

Operation of ANN

As it is shown in the topology diagrams above, the connections between two neurons and the direction of information flow is represented by the arrows and the direction of the arrows.

The number on each arrow indicates the weight of this connection which takes control of the signal passes through.

If the output of the network appears to be as expected and correct, weights are not designed to be altered. Only when an unexpected output appears, the weights are then adjusted by the system to improve the subsequent results.

ANNs are capable of learning and they need to be trained. There are several learning strategies:

- **Supervised learning** is the machine learning task of inferring a function from labeled training data. A 'teacher' is involved which has more knowledge than the neural network itself. During the training process, pre-defined set of training examples (traning data) are fed into the model. A set of training example consists of an input object which is normally a vector and its corresponding expected output value which alternatively can be called supervisory signal. An inferred function is produced after analyzing the training data by following certain supervised learning algorithm. New examples are then mapped using this inferred function. Algorithm will be able to put correct class labels for any further incoming unknown instances. This is only possible when learning algorithm generalizes from the training data to future unknown situation in a well-designed way.

- **Unsupervised Learning** infers a function to find the unknown relationship network topology from data which are unlabeled. Unlabeled means there is no classification or categorization during the observation process. No example data set are required in unsupervised learning. This method is usually used to search for hidden patterns. Also, because there of the unsupervised nature, there is no way to evaluate the accuracy of the trained structure which is output by the relevant algorithm

- **Reinforcement Learning** is a strategy built on observation. The ANN makes a decision by observing its environment. If the observation is negative, the network adjusts its weights to be able to make a different required decision the next time.

Back Propagation

The back propagation algorithm was originally introduced in the 1970s, but its importance wasn't fully appreciated until (replace with that reference)a famous 1986 paper by David Rumelhart, Geoffrey Hinton, and Ronald Williams. That paper describes several neural networks where back propagation works far faster than earlier approaches to learning, making it possible to use neural nets to solve problems which had previously been insoluble. Today, the back propagation algorithm is the workhorse of learning in neural networks.

The backward propagation of errors or backpropagation is widely used in ANN training procedure and used in conjunction with an optimization method e.g. gradient descent. The algorithm has two phase cycle, propagation and weight update and it iterates this cycle over and over again. The procedure starts by propagating forward a presented input vector through layers (including hidden layers) until it reaches the output layer. Comparison of the network output and expected output by applying loss function takes place in the next step. Each single neuron in the output layer produces an error value based on loss function calculation. Finally the backward propagation process takes the error values to the input layer, layer by layer, from the last layer backwards. This process only stops until each neuron has an associated error value which roughly represents its contribution to the original output [74].

Back Propagation networks are ideal for simple Pattern Recognition and Mapping Tasks.

3.3.2 Neural Network Structure

Artificial Neural Network (ANN) can be trained with data sets with or without supervisor to solve literally any realistic problems. With no requirement of any specific programming to fit the category of events related, the trained ANN model can be used to predict the output of the new data set presented based on "experience" under the condition that the new data sets stay in the same problem range as previous. Over the past decade, the number of ANN application fields has vastly grown particularly in pattern recognition. A large variety of possible ANN applications now exist for non-computer specialists. Therefore, with only a very modest knowledge of the theory behind ANNs, it is possible to tackle complicated problems in a researcher's own area of speciality with the ANN technique.

Although ANN is super powerful and there is no need of any human activity during and after training. Also, it can be used to solve any statistical problem in this universe. However, it requires a start-up force to make it rolling towards the target. This force is the design of the neural network structure.

As we discussed earlier in this chapter, multilayer networks can be used to approximate almost any function, if we have enough neurons in the hidden layers. However, we cannot say, in general, how many layers or how many neurons are necessary for adequate performance. But ideally, we want our system to look like something as shown in figure 3.8:

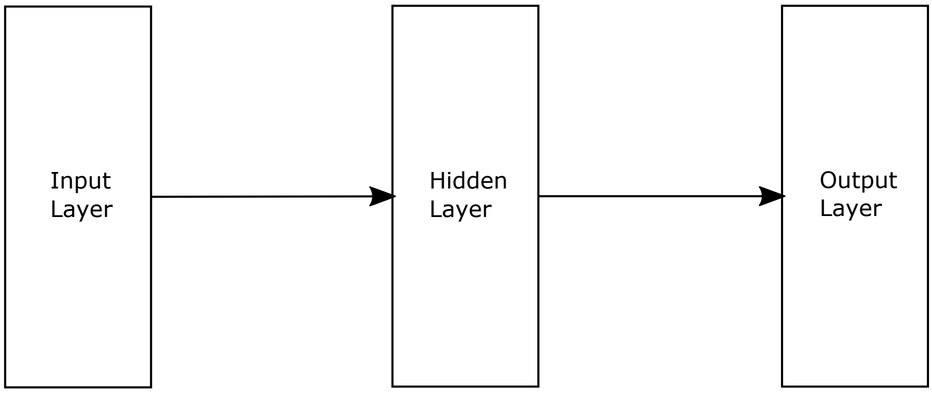

Fig. 3.8 General Neural Network Structure

Where input layer should include all the potential impact factors of the output. And because of the non-linear feature of the room temperature flow, hidden layer(s) are necessary for neural network training. The output layer can be simple at this stage which is the level of change of the temperature in next time slot. Problem specifications help define the network in the following ways:

- Number of network inputs = number of problem inputs.
- Number of neurons in output layer = number of problem outputs.
- Output layer transfer function choice at least partly determined by problem specification of the outputs

Then we formed the network structure is shown as in figure 3.9:

In Figure 3.9, the input layer consists of all the possible impact factors including the current room temperature, current heating output level, outside environmental impact and human activity. Current room temperature apparently affects the temperature change in an Inversely proportional way and it sets the upper and lower bound of the room temperature.

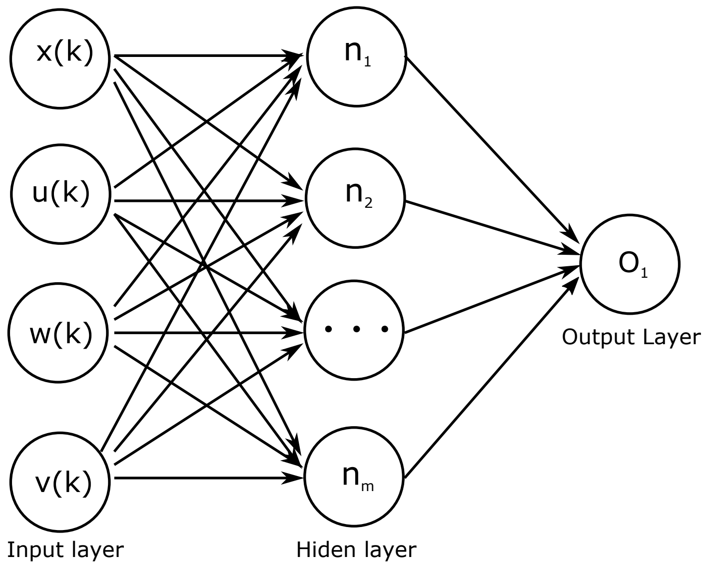

Fig. 3.9 Neural Network Structure for Heating Prediction

This is easy to understand, when the current room temperature is high or low enough, it is very unlikely to go any higher or lower. Current heating output normally has a significant impact on the output. This is also quite natural since heating is the main resource to change the room temperature. Outside environment mainly includes weather, outside temperature and air flow speed. These parameters may change slowly but still affect the indoor temperature. Last but not least, the human activity sometimes can also have significant impact on room temperature. Imaging someone opens a window and this will lower the room temperature in an ultra-fast way. Other typical human activities are cooking, exercising, people gathering etc. However, these parameters are hard to be modeled. For example, weather is a very ambiguous concept, how can we map it into something understandable by neural network?

3.3.3 Mapping of Parameters

To map the parameters into something neural network can understand, ideally, the input value for each neuron should be between -1 and 1. One of the method is to map the ambiguous inputs into some reasonable values as shown in figure 3.10:

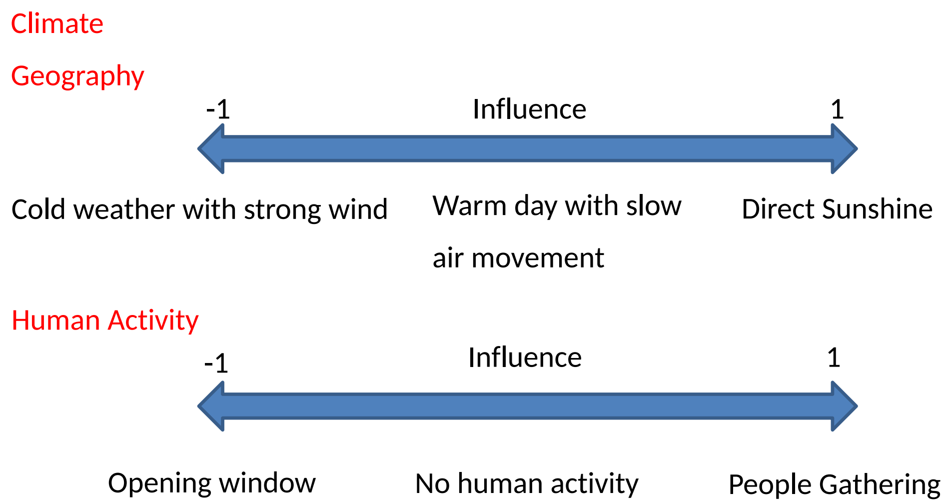

Fig. 3.10 Mapping of Ambiguous Parameters

However, how to determine the value of these parameters becomes extremely hard, one possible way is to evaluate the value of parameters based on experience. For example, when it is cloudy with slow air movement, the impact on weather can be mutual so the impact level can be around -0.1 which means it has a slightly negative effect on the room temperature. However, this approach is not quite scientific since this number is based only on human's "experience". The number can sometimes be correct sometimes not. Finding a way to evaluate these ambiguous parameters is quite challenging.

Thus, as shown in Figure 3.11, we introduced a self-learning method to evaluate the impact on these ambiguous parameters. This structure allows the network to train itself to

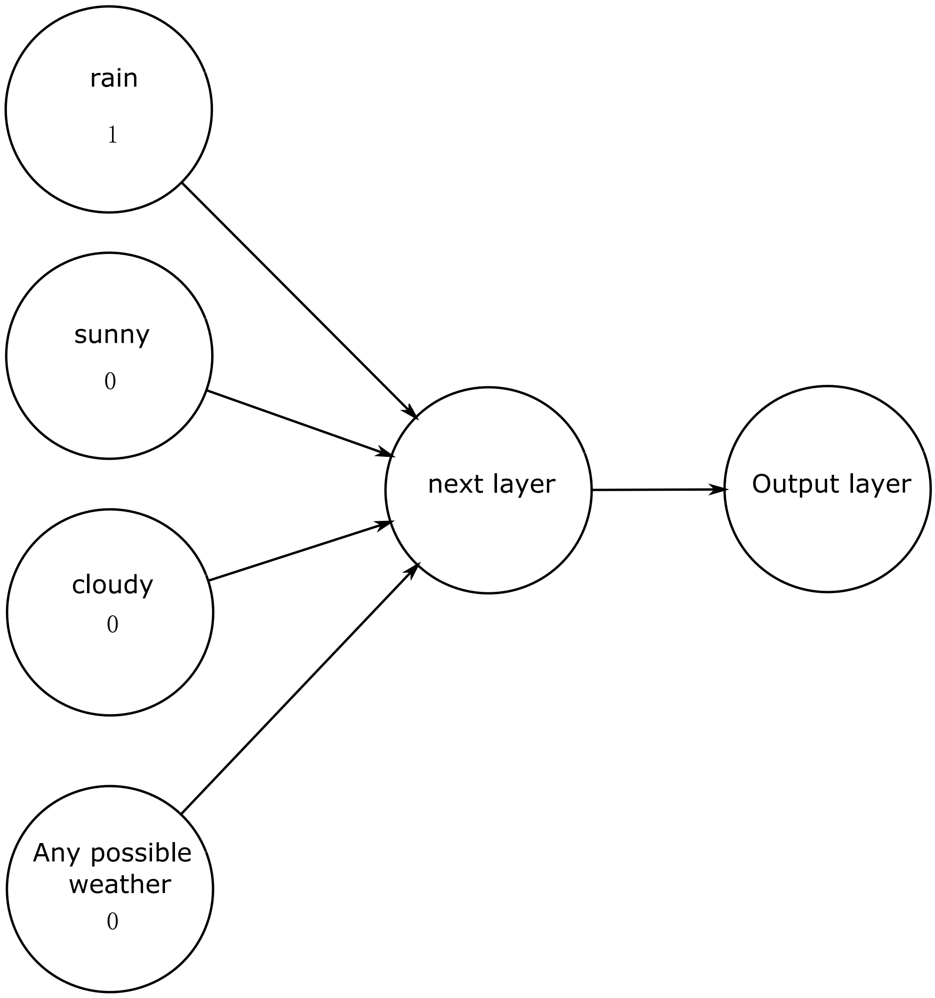

Fig. 3.11 Training of Weather Parameters

get the impact level for each individual possible input scenario. There several advantages of this method.

- It can take as many possible inputs. One neural represents one possible scenario.
- It can deal with any customized scenario. For example, “sunny day but with strong wind”. Once this scenario happened, then next time it can be most likely accurately predicted.

- This approach is much more scientific and the number is learning using standard neural network learning process. The weight connected to each neuron represents it's potential contribution to the final output.

Normalise the Current Temperature Inputs

$$\frac{x - \min(x)}{max\,(x) - min\,(x)}$$

We use Feature scaling to normalize the current temperature inputs which is to divide it by its maximum possible value in the training set. By this way, it's mapped into a space of $[-1, 1]$. Feature standardization makes the values of each feature in the data have zero-mean (when subtracting the mean in the numerator) and unit-variance.

Mapping the Heating Impact

Typical heating outputs are discrete values ranging from 0 to 100 percent, indicating the level of hot water valve opening or the output level of electrical heating radiator. There are two possible ways to map this kind of parameter, first one is also using standard feature scale as the current temperature. However, this method maps the output level in a linear way, which in many cases is not true. Most of times, output impact is not linearly proportional to its corresponding output level. Not to mention that sometimes the water value opening level or electrical heating output level are not even precise in reality. So we proposed a similar self-learning method as what we used for environmental parameters.

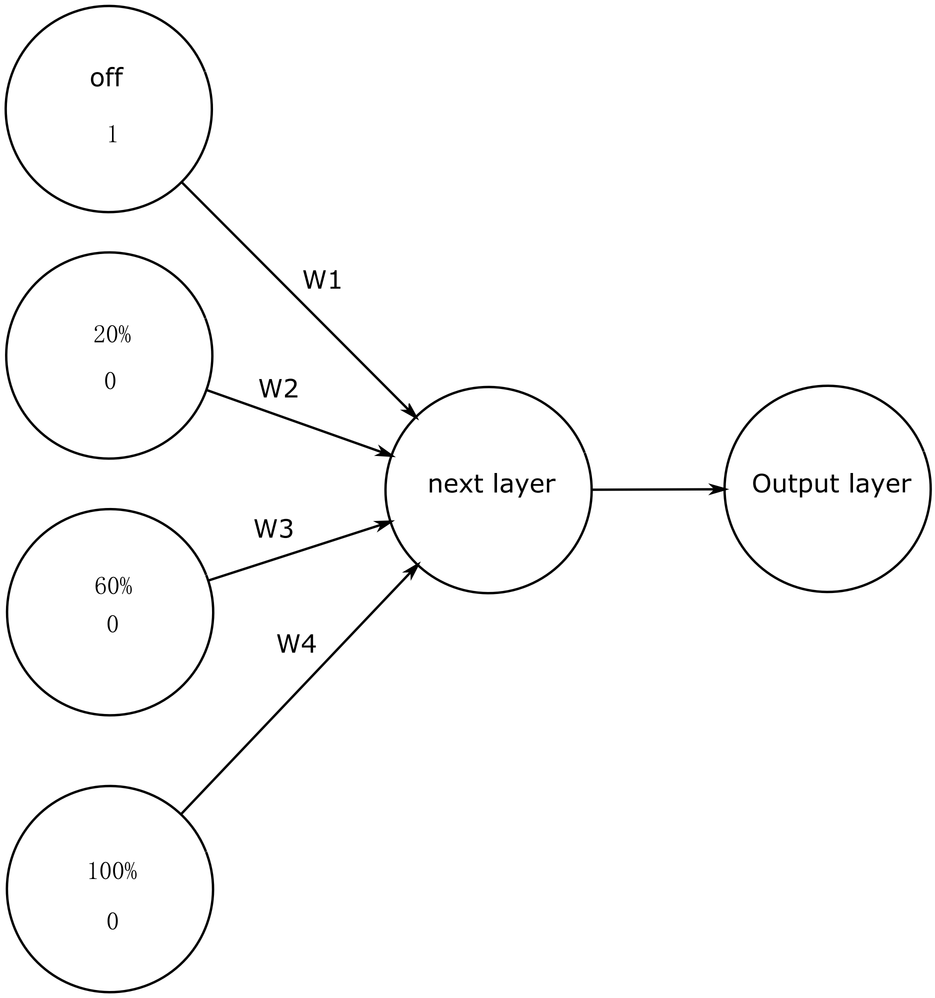

Fig. 3.12 Training of Heating Parameters

As shown in Fig. 3.12, since the heating output is discrete, we created several input neurons each represents on possible TRV output value. The weight connected to each possible input indicates the corresponding impact factor of it. For example, if 40% of TRV output is on, that neuron will be fired with value 1, others will be inactive with value 0. By this means, the model can be robust and correctly mapping all possible heating input into something understandable to itself. Similar approach will be also used for multiple heating impacts and human behaviour training.

Mapping of human behaviour

Human behavior can sometimes have significant impact on room temperature. Typical behaviors include opening window, cooking and indoor exercising etc. These behaviours are extremely hard to model into a mathematical value in conventional methods. We propose a similar method as current temperature and room output level. By this way, each neuron represents one possible human behavior. During the training session, depending on the number of possible human behaviours in the training data, same number of neurons are added to the input set to produce the ability to train the data correctly corresponding to different scenarios.

As shown in figure 3.13, for each possible human behaviour (customizable by different type of user), one input neuron is created. If an event is triggered, the input is set to 1, otherwise 0. Its corresponding weight indicates the level of impact on the final output.

3.3.4 Generalization of Neural Network

One of the key issues in designing a multilayer network is determining the number of neurons to use. Overfitting occurs when the error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations.

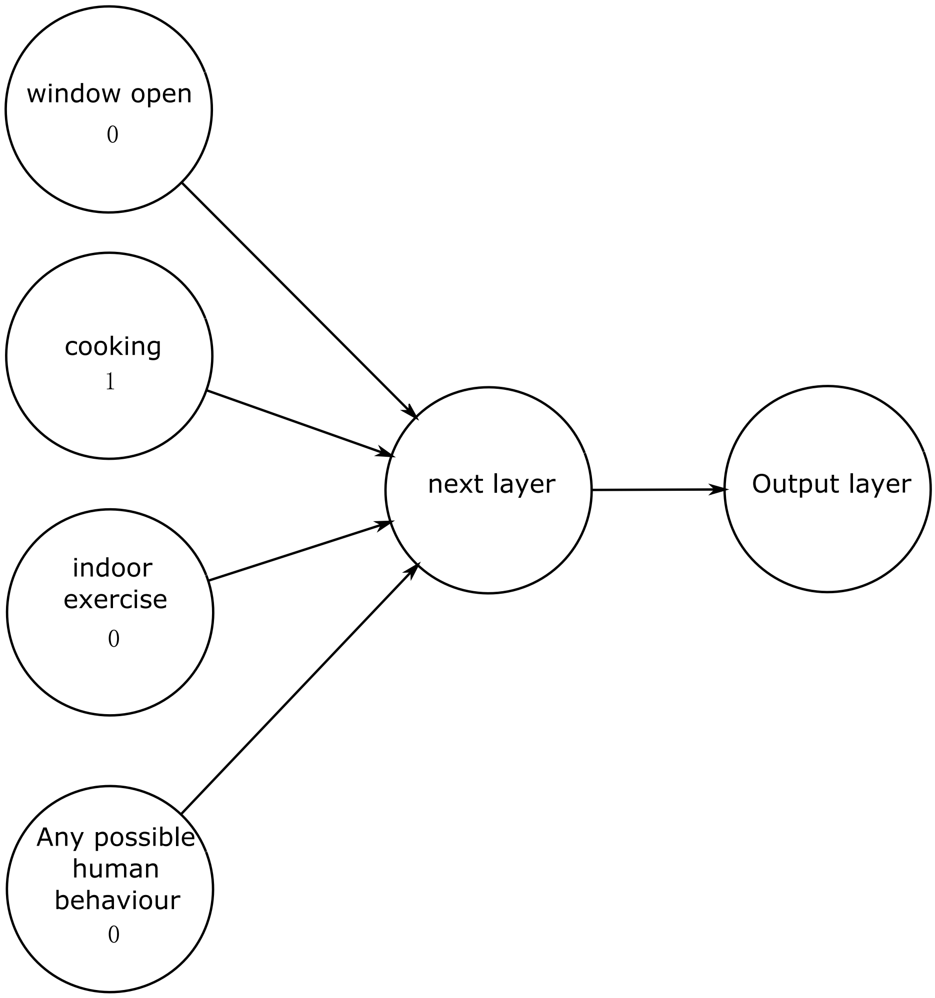

Fig. 3.13 Mapping of Human Behaviour

The following figure 3.14 shows the response of a $1-20-1$ neural network that has been trained to approximate a noisy sine function. The underlying sine function is shown by the dotted line, the noisy measurements are given by the + symbols, and the neural network response is given by the solid line. Clearly this network has overfitted the data and will not generalize well.

The complexity of a neural network is determined by the number of free parameters that it has (weights and biases), which in turn is determined by the number of neurons. If

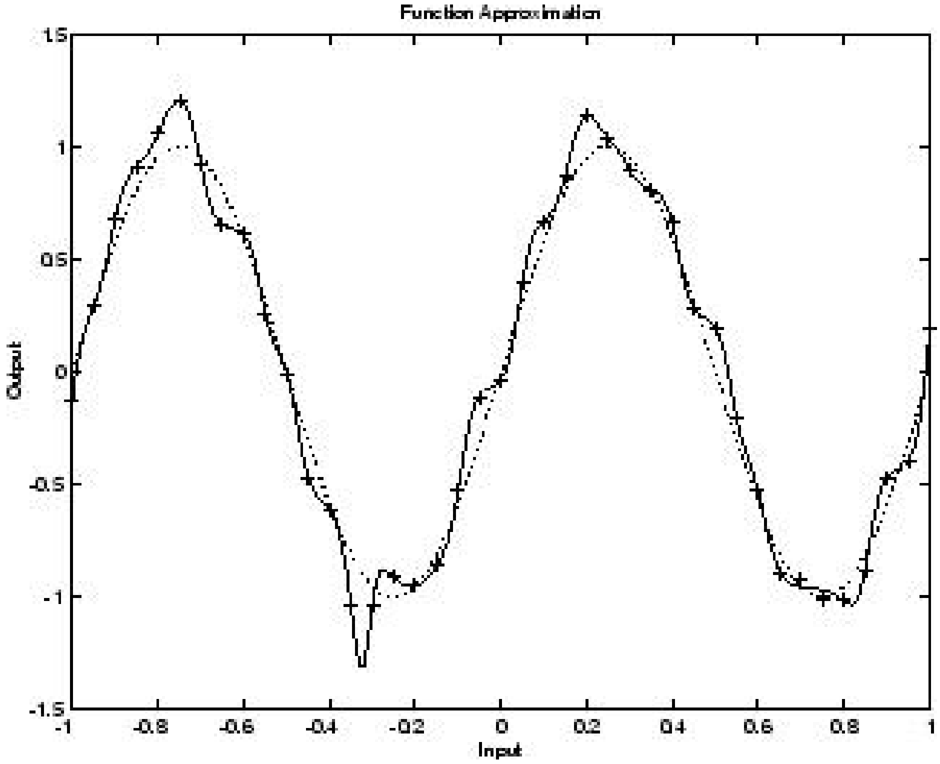

Fig. 3.14 Sample of Neural Network Generalization [75]

a network is too complex for a given data set, then it is likely to overfit and to have poor generalization.

In this session we will see that we can adjust the complexity of a network to fit the complexity of the data. In addition, this can be done without changing the number of neurons. We can adjust the effective number of free parameters without changing the actual number of free parameters.

To seek for the simplest neural network structure which can demonstrate the data is the key method that will be used to achieve good generalization. This is a variation of a principle called *Ockham's razor*, which is named after the English logician William of Ockham, who worked in the 14th Century. The principle points out that the more complex the model is, the greater the possibility for errors.

In terms of neural networks, the simplest model is the one that contains the smallest number of free parameters (weights and biases), or, equivalently, the smallest number of neurons. To find a network that generalizes well, we need to find the simplest network that fits the data.

There are at least five different approaches that people have used to produce simple networks: growing, pruning, global searches, regularization, and early stopping. Growing methods start with no neurons in the network and then add neurons until the performance is adequate. Pruning methods start with large networks, which likely overfit, and then remove neurons (or weights) one at a time until the performance degrades significantly.Global searches, such as genetic algorithms, search the space of all possible network architectures to locate the simplest model that explains the data.

The final two approaches, regularization and early stopping, keep the network small by constraining the magnitude of the network weights, rather than by constraining the number of network weights. In this project, we will use early stop method to generalize the neural network structure.

Early stopping is treated as a simplest method for improving generalization. That is why it is used in our model. The concept of this method is that with the progress of training going forward, more and more of the weights in the network are used, until all weights are fully used when training reaches a minimum of the error surface. When the number of iteration of training are increased, the complexity of the resulting network is increasing at the same time. The network will effectively be using fewer parameters and less likely to overfit if the training process is stopped before the minimum is reached [76].

To effectively perform early stopping in our model, a timing to stop the training is needed. Cross-validation is a method that uses validation set to decide when to stop [77]. The available data is divided into two parts: a training set and a validation set. The training set performs normally to compute gradients and to determine the weight update during each iteration. On another hand, the validation set is used to indicate what is happening to the network function "in between"the training points, and during the training process its error are watched. The training stops when the error on the validation set increases for a few iterations. After that, trained network weights are finalized with the weights which produced the minimum error on the validation set.

This process is illustrated in figure 3.15 The graph at the bottom of this figure shows the progress of the training and validation performance indices, (the sum squared errors), during training. Although the training error continues to go down throughout the training process, a minimum of the validation error occurs at the point labeled "a," which corresponds to training iteration 14. The graph at the upper left shows the network response at this early stopping point. The resulting network provides a good fit to the true function. The graph at the upper right demonstrates the network response if we continue to train to point "b," where the validation error has increased and the network is overfitting.

3.3.5 Backpropagation

The Backpropagation algorithm is a supervised learning method for multilayer feed-forward networks from the field of Artificial Neural Networks.

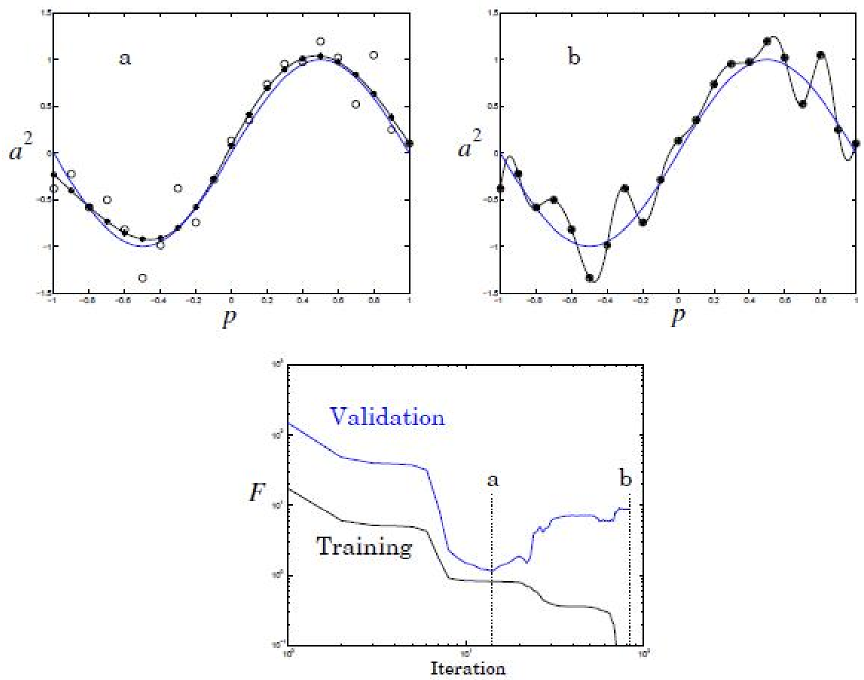

Fig. 3.15 Early Stopping Process

The principle of the backpropagation approach is to model a given function by modifying internal weightings of input signals to produce an expected output signal. The system is trained using a supervised learning method, where the error between the system's output and a known expected output is presented to the system and used to modify its internal state.

Technically, the backpropagation algorithm is a method for training the weights in a multilayer feed-forward neural network. As such, it requires a network structure to be defined of one or more layers where one layer is fully connected to the next layer. Backpropagation can be used for both classification and regression problems.

Phase 1: propagation

Each propagation involves following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the network's output value(s).

2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas (the difference between the targeted and actual output values) of all output and hidden neurons.

Phase 2: weights update

For each weight, the following steps must be followed:

1. The weight's output delta and input activation are multiplied to find the gradient of the weight.

2. A ratio (percentage) of the weight's gradient is subtracted from the weight.

This ratio (percentage) influences the speed and quality of learning; it is called the *learning rate*. The greater the ratio, the faster the neuron trains, but the lower the ratio, the more accurate the training is. The sign of the gradient of a weight indicates whether the error varies directly with, or inversely to, the weight. Therefore, the weight must be updated in the opposite direction, "descending" the gradient.

Phases 1 and 2 are repeated until the performance of the network is satisfactory. To implement the algorithm above, explicit formulas are required for the gradient of the function

Backpropagation Algorithm

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Algorithm 1 Backpropagation Algorithm

```
procedure BACKPROPAGATION
    initialization: initialize network weights (often small random values)
    while Any examples classified correctly or another stopping criterion not satisfied do
        for each training example named ex.
        prediction = neural-net-output(network, ex)
        actual = teacher - output(ex)
        compute error (prediction - actual) at the output units
        compute for all weights from hidden layer to output layer
        compute for all weights from input layer to hidden layer
        update network weights
    end while
end procedure
```

3.4 Artificial Neural Network Based Training Algorithm

We proposed a modified ANN based algorithm to train the model where only the changed parameters get the right to be updated.

Work Flow Diagram

Algorithm 2 Artificial Neural Network Based Training Algorithm

procedure GET ACCURATE PARAMETERS
    Initialisation: get a set of initial values of Weight W.
    Get the predicted temperature T and collected real temperature R
    while the absolute error between T and R is bigger than the pre-set threshold, do **do**
        for i from 1 to 5,do **do**
            if The parameter changes from the last time slot **then**
                update the weight of this parameter using standard error correction method.
            end if
            Calculate the updated prediction value
            Compare with the real value, update error value
        end for
    end while
end procedure

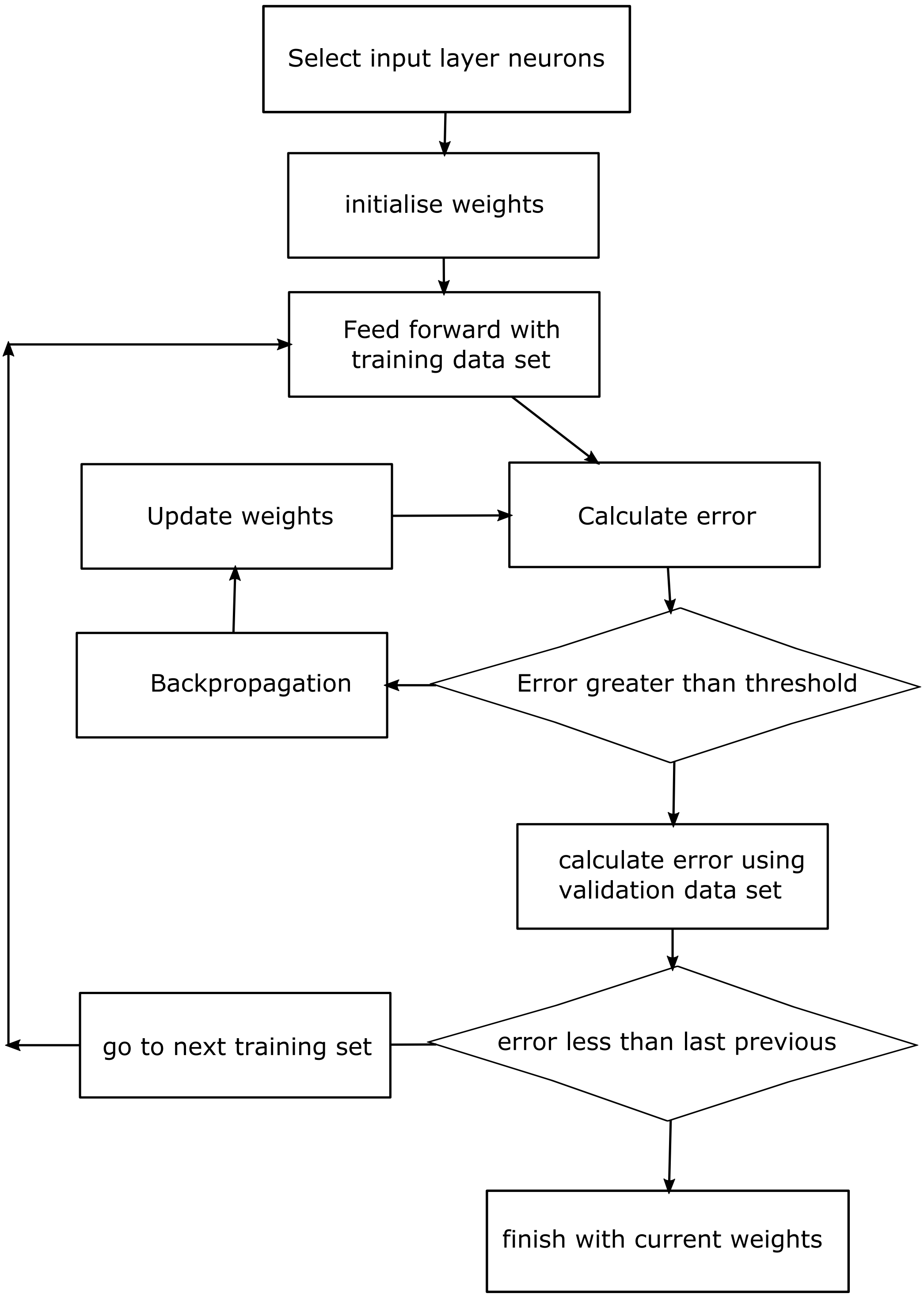

Fig. 3.16 Work Flow Diagram

3.5 Results

3.5.1 Experimental Setup

Our experimental data is collected from a typical UK residential house located in Derby which has two floors. There is an entrance lounge, a kitchen, a living room and a stair well on the ground floor. First Floor contains two bedrooms, one bathroom, one lounge and one open lounge area. Remote controllable TRVs are installed in the rooms marked as in figure 3.17 and figure 3.18.

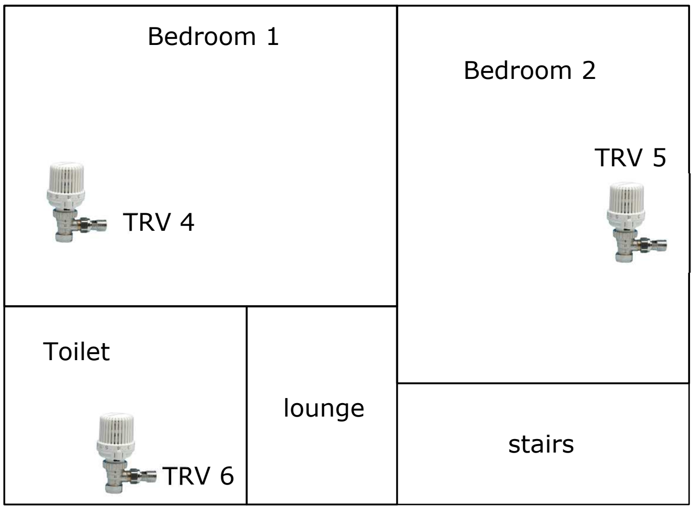

Fig. 3.17 Upstairs Layout

Data Collection

Figure 3.23 shows the data we used in our simulation. There are totally six TRVs installed in the house, the data collected from them are shown in the sub-figures. From the figures we can see that every room has its own heating schedule and heating output. Some of them are affected by other heating resources (rapid temperature raise with no heating output on).

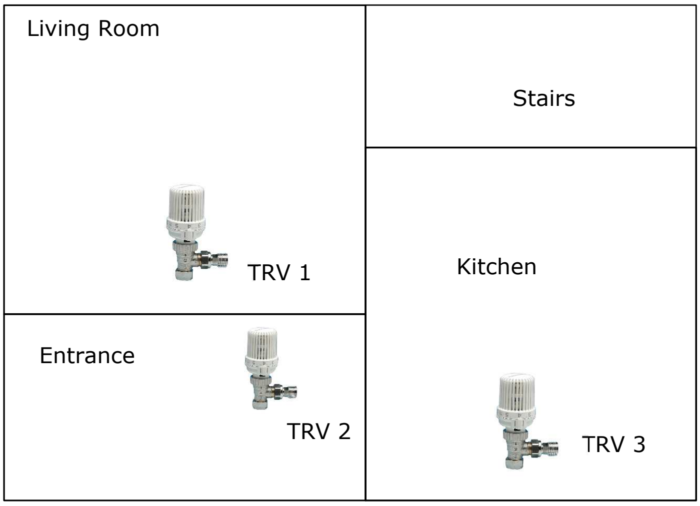

Fig. 3.18 Downstairs Layout

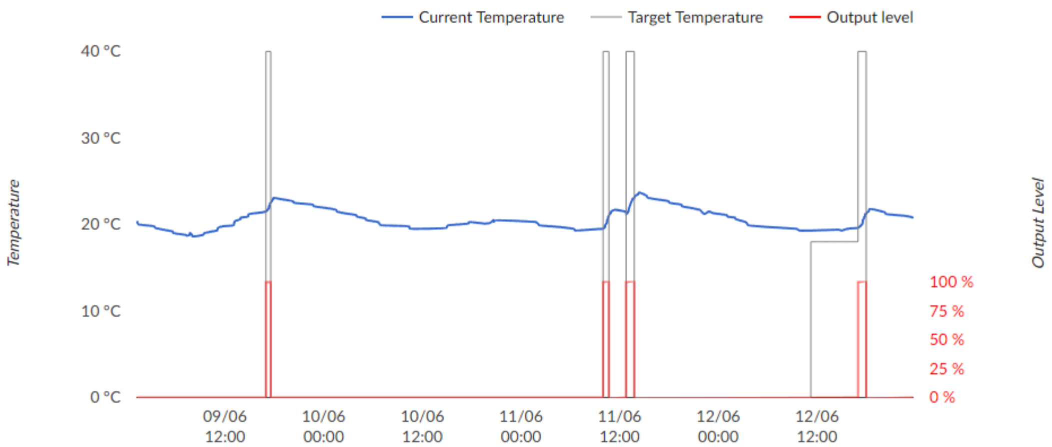

Fig. 3.19 Downstairs Lounge

Also we collected the weather data for these days using the local weather report service to use as input for weather impact training. There is also a observable impact of time of the day (TOD) on the temperature change.

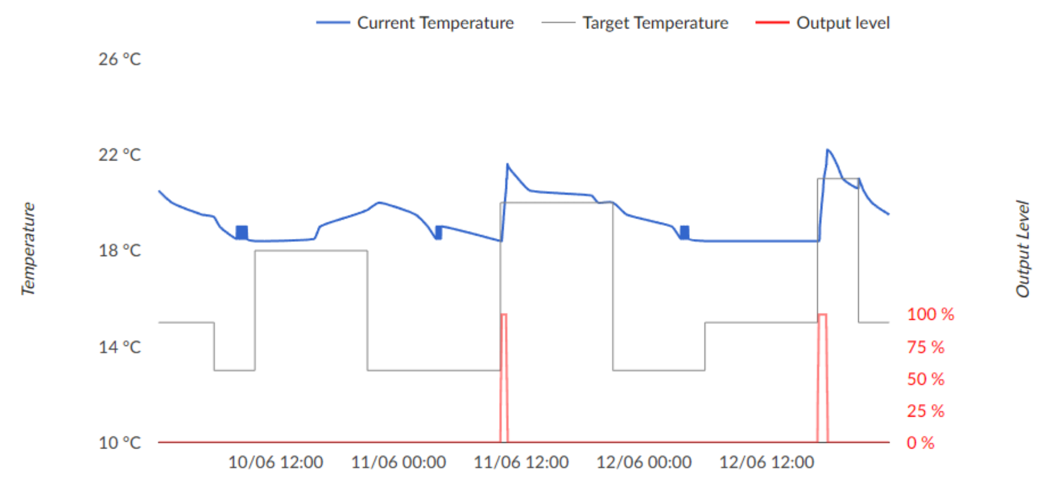

Fig. 3.20 Downstairs Living Room

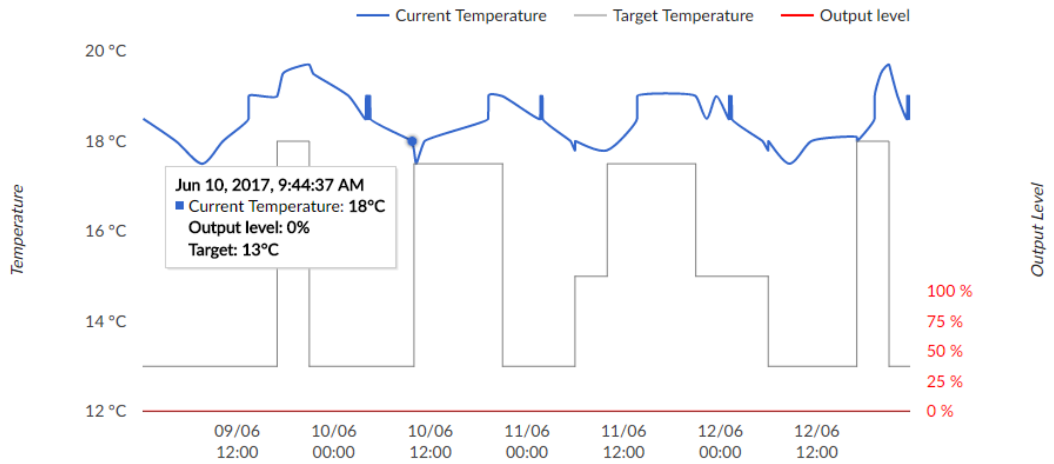

Fig. 3.21 Kitchen

3.5.2 Parameter Weights Training Results

We used downstairs living room temperature training as an example. Other rooms use duplicated procedure as the living room. The weather impact is shown in figure 3.25. From the figure we can see that different weather conditions have different impact on the room temperature change. Direct sunshine shows biggest impact on the temperature change which has the value of around 0.5 positive. Others have relatively less impact on that.

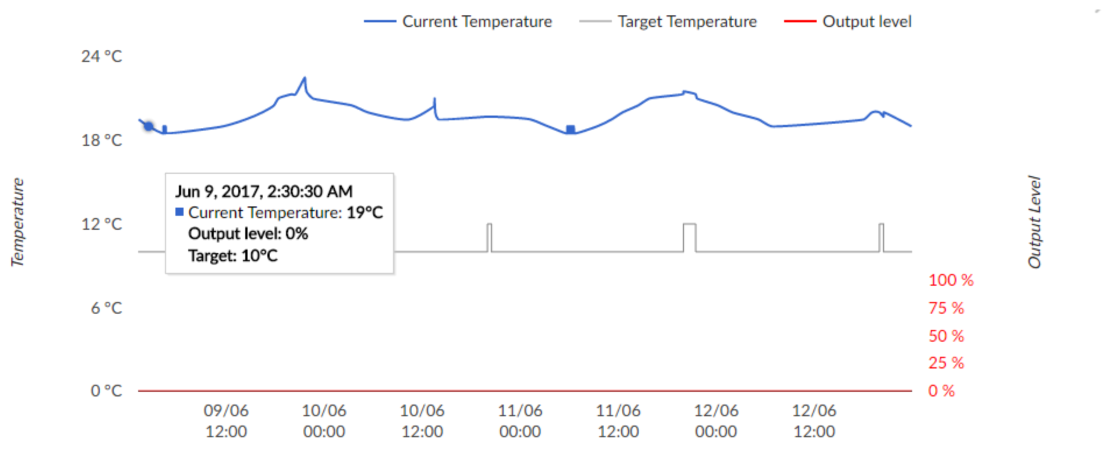

Fig. 3.22 Upstairs Lounge

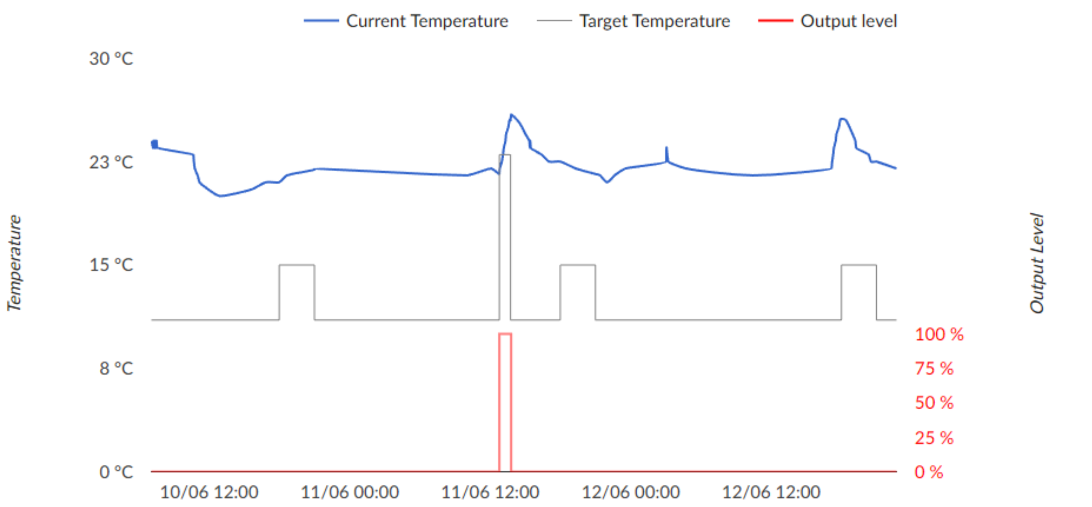

Fig. 3.23 Bedroom 2

Figure 3.26 shows the impact on multiple TRVs in the house. In the previous session we mentioned that because of the nature of the house structure. Neighbouring heating resource may have a potential impact to different room temperature changes. From the figure we can see that the living room temperature is also affected by the TRVs in the downstairs lounge with main impact of their own TRVs. This feature detect method can also be used to detect

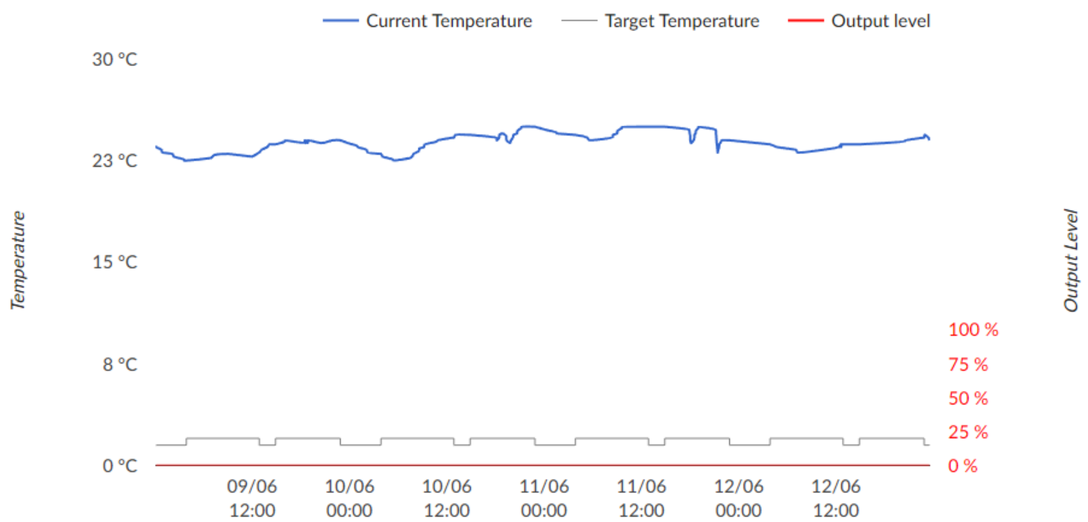

Fig. 3.24 Bedroom 1

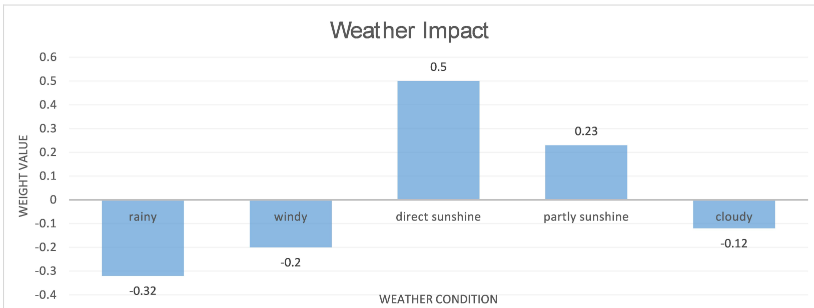

Fig. 3.25 Weather Impact on Living Room

any faulty condition of TRVs. If the TRVs impact is very little even when it has been turned on to the maximum level then it is very likely to be out of order.

Figure 3.27 shows the time of day impact on the room temperature, time1 is between 00:00AM - 6:00AM, time2 is 6:00AM - 12:00PM, time3 is 12:00PM to 5:00 PM, time4 from 5:00PM to 00:00AM. This normally reflects a mixed impact of outside temperature and environmental change.

Figure 3.28 shows the impact of TRV output level on living room temperature. According to the training results, the impact is not linearly proportional to the output level.

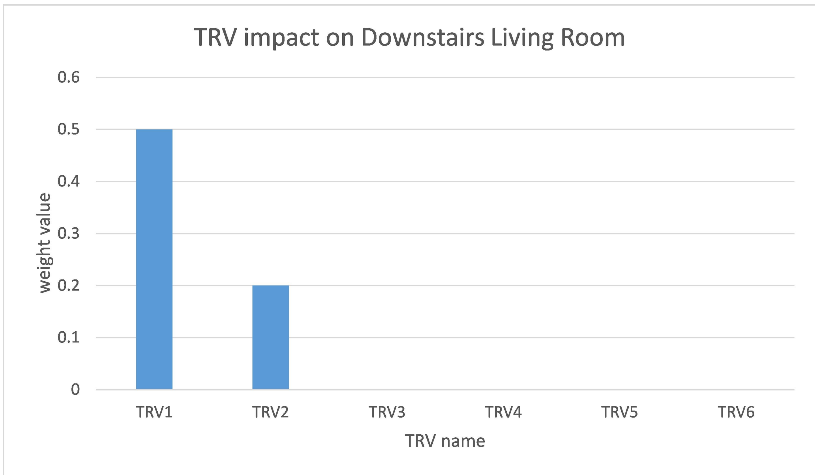

Fig. 3.26 Multiple TRVs Impact on Living Room

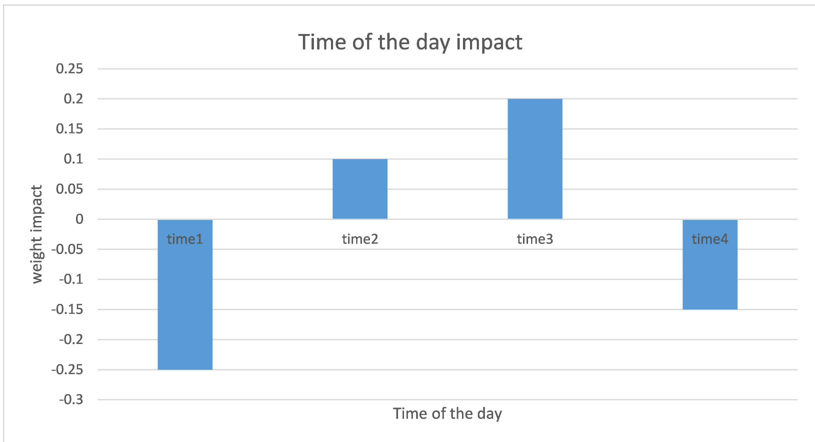

Fig. 3.27 Time of the Day Impact on Living Room

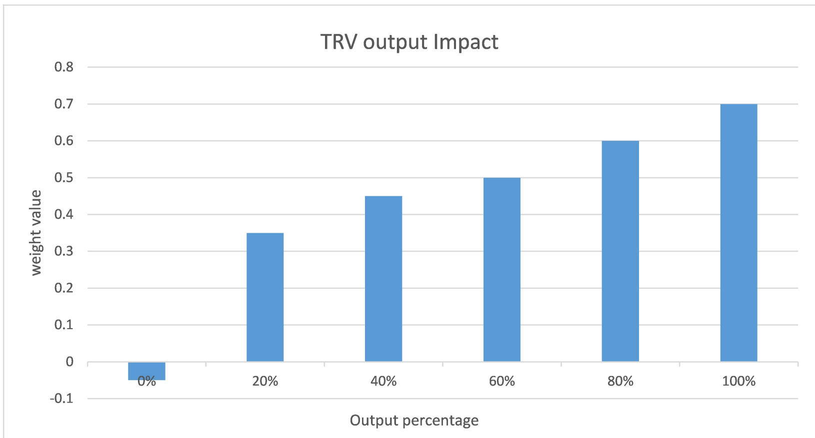

Fig. 3.28 TRV output level Impact on Living Room

3.5.3 Simulation Performance

Figure 3.29 shows the Mean Square Error of the real weights and trained model weights. From the figure we can see that the convergence speed is quite fast which totally satisfies our requirements for residential using scenario. Mean Square Error (MSE) is an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations—that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. Other options are statistical functions such as Frequentist expected loss and Bayesian expected loss. We chose to use MSE because of the simplicity it creates. Figure 3.30 shows

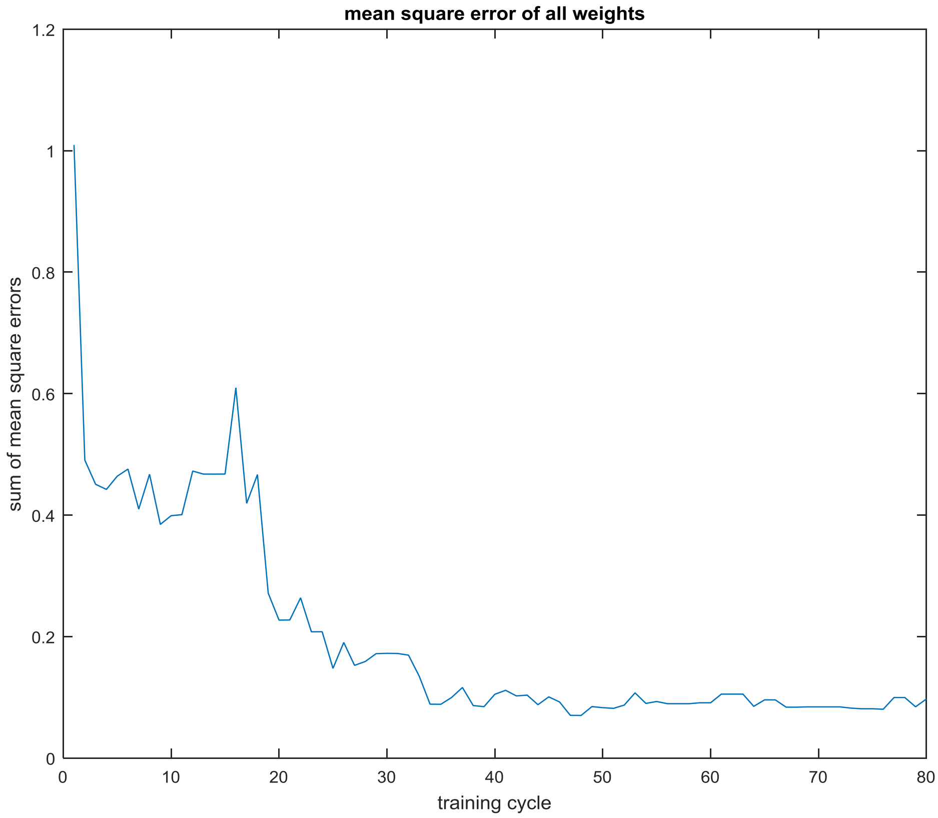

Fig. 3.29 The Mean Square Error of Weights and Real Weights

the prediction temperature curve and the measured temperature curve. The prediction can be quite accurate after few time slots of training. Although with large change of environment, the prediction value can vary. The blue line indicates the obtained operational data from the TRV in the living room. The red line indicates the predicted value of the room temperature. Since we have considered most of the potential impacts, the prediction value is quite close to the actual value.

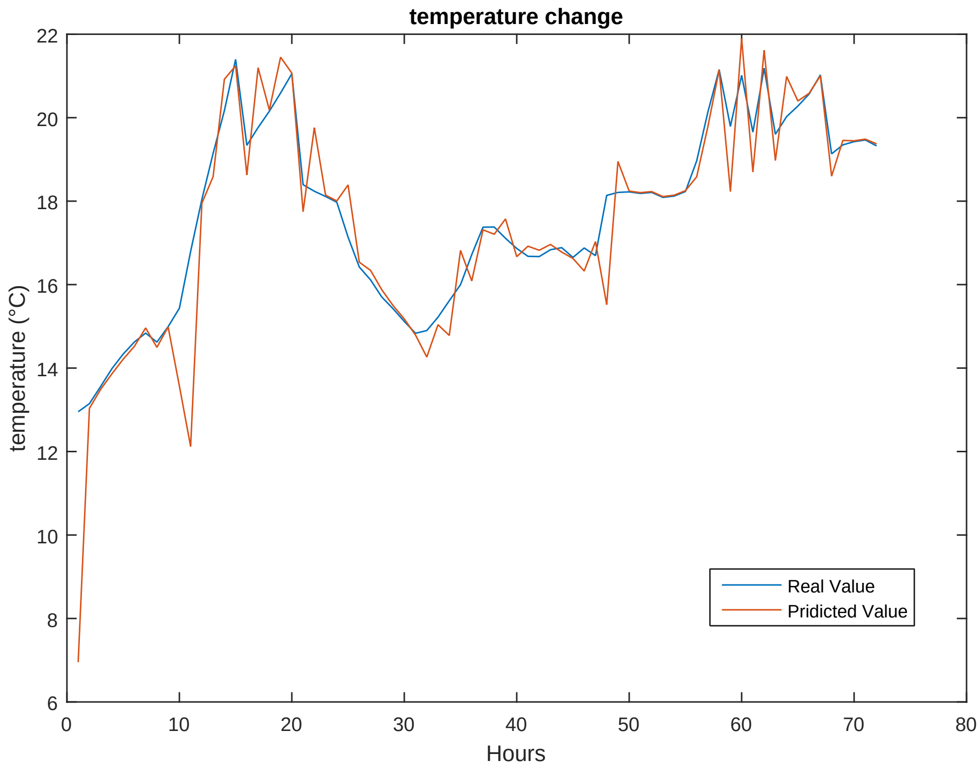

Fig. 3.30 Predicted and Actual Temperature Curve

Figure 3.31 shows the heating operation with the prediction of the temperature. Without the users' operation, our system can operate themselves to adjust the room temperature to a suitable condition.

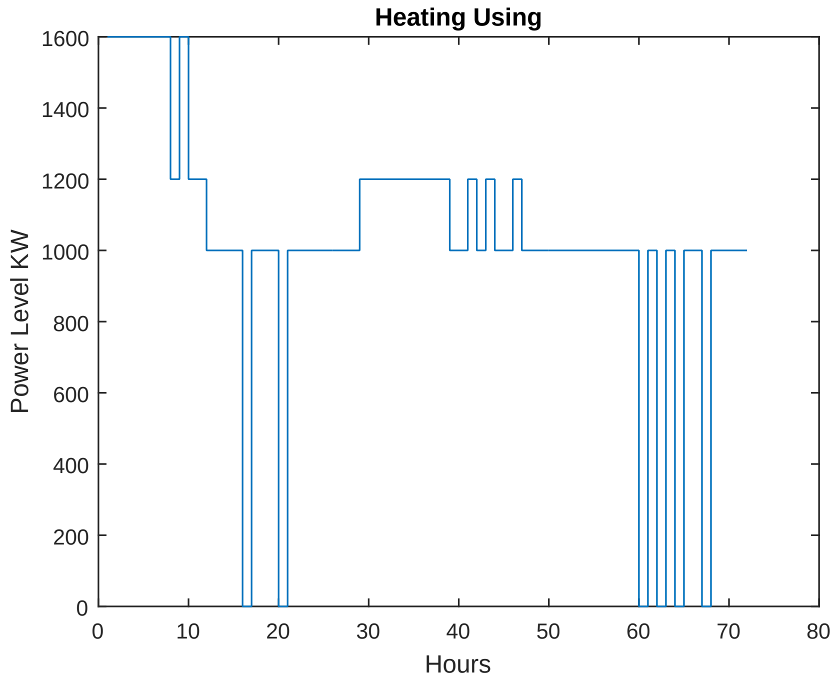

Fig. 3.31 Heating Operation

3.6 Summary

In this chapter we proposed a mathematical model for building thermal dynamics which considers both the house heating system and environmental impacts. An innovative way to map ambiguous parameters are shown to fit the parameters into a valid neuron network training and prediction model. Also, we considered multiple heating resource impact on neighbouring rooms. To determine the weights of the model, we proposed a Artificial Neural Network based machine learning algorithm and a cycle based learning procedure. From the results we confirmed our method not only provides a good performance on the accuracy of prediction, also it has a fast convergence speed which is required by the residential house scenario.

Chapter 4

Optimisation on Total House Energy Usage

4.1 Introduction

The legacy electricity plant and distribution system has been existed for over 50 years. Although the progress in many fields of science has been comparatively rapid, changes in the distribution grids proceeded only moderately. Recently, a lot of challenges are revealed within the energy industry for example the peak power demand has increased for a big level and this requires more effect on balancing the electricity demand and generation. Additionally, economic and environmental reasons will cause distribution companies to consider more complex power balance scenarios, and currently, it is also believed that the next generation power grid will be green in terms of the environmental impact. At present, such systems are generally known as smart grids.

The demand-side management (DSM) approach proposed in the 1980s is a modification of user-generated energy demand preferences performed to optimize overall energy consumption [78]. One of the most fundamental requirements for the DSM is consumption shifting (thus, for example, electric water heater warming or electric vehicle charging can be carried out during late night or early morning hours, namely when there is much less demand than in the peak period). Less intensive requirements on the grid facilitate an increase in the energy delivery stability and grid lifetime, and they reduce the need of massive investment in the grid hierarchy.

Residential load scheduling is a demand side energy management technique which allows user to adjust their energy usage schedule to fit certain design intents such as to minimise the energy bill or maximise their comfort needs.

4.2 System Model

4.2.1 Residential Consumers

We consider a residential unit that participates in a real-time pricing program. We divide the considered 24-hour period into N equal scheduling time slots each with the equal length of t. For simplicity, we assume that the length of time slot is shorter than one hour and the the electricity price at time slot h is $C(h)$ (£/KWh). Let $A = [A1, A2, A3]$ denote the set of appliances in this unit, which may include washer, drier, plug-in hybrid electric vehicle(PHEV), etc. $A1$ represents Heating Ventilation and air conditioning system (HVAC). $A2$ represents other controllable appliances. $A3$ represents the remaining non-controllable appliances. For each appliance $a \in A$, there should be an energy consumption scheduling vector x_a:

$$x_a = [x_a^1, \ldots, x_a^H] \tag{4.1}$$

where H is the time index with integer value from 1 to 24 representing 24 hours in real life.

Thermal comfort is related directly to the life comfort of user. We assume the user requires that the inddor temperature fall in a pre-determined rage $\left[T^r_{\min}, T^r_{\max}\right]$ during a predefined time window $[\alpha, \beta]$ when the household is occupied. Let T^r_h be the inddor temperature captured at time slot h, then the comfort constraint can be expressed as:

$$T^r_{\min} \leq T^r_h \leq T^r_{\max} \tag{4.2}$$

We propose to employ a temperature prediction method mentioned in Chapter 3 for HVAC scheduling, where all the prediction on temperature can be done based on historical data and real-time data captured.

$$x(k+1) = ax(k) - bu(k) + cw(k) + dv(k) + \varepsilon \tag{4.3}$$

let $\sigma \in \{1, 2, ..., 24\}$ represent the hourly index. We assume that there are energy consumption threshold $E^{\max}_{\sigma}$:

$$\sum_{a \in A} x_a^h \leq E^{\max}_{\sigma} \tag{4.4}$$

Some house hold loads can be operated at any level from the set of power levels (*e.g.* an Electrical Vehicle may have a set of charge rates. We define the set of power levels for these loads as:

$$x_a^h \in \{x_a^1, \ldots, x_a^n\} \tag{4.5}$$

The power level consumption of some households can take continuous values.

$$x_a^{Min} \leq x_a^h \leq x_a^{Max} \tag{4.6}$$

4.2.2 Pricing Model

We assumed that there are multiple energy retailers in this area of which each retailer can both sell energy at a selling price and buy back energy at a lower price compared to the selling price.

The retailers use real-time pricing tariff combined with inclining block rates, in which prices increase by the total amount of energy consumption. The pricing tariff has fixed energy prices at different times of the day:

$$P_s^h(x^h) = \left\{ \begin{array}{c} a^h, 0 \leq x^h \leq c^h \\ \\ b^h, x^h > c^h \end{array} \right\} \tag{4.7}$$

where P_s^h is the selling price, c^h is the pricing threshold.

4.2.3 Renewable Energy Generation

Total renewable energy generation at time t is denoted by G_h where

$$G_h = GC_h + GB_h + GS_h \tag{4.8}$$

where GC_h is the renewable energy consumed by appliances at time t. GB_h is the renewable energy sell back to the grid. GS_h is the energy that goes into energy storage.

$$GC_h = \left\{ \begin{array}{c} G^h, x^h \geq G^h \\ G^h - x^h, x^h < G^h \end{array} \right\} \tag{4.9}$$

$$GS_h = \left\{ \begin{array}{c} 0, x^h \geq G^h \\ G^h - x^h, x^h < G^h \cap S_h < S_{\max} \end{array} \right\} \tag{4.10}$$

$$GB_h = G_h - GC_h - GS_h \tag{4.11}$$

Energy Storage and Sell Back

The energy generated by renewable energy plants can be either stored in the storage when it is already enough for the current load requirement or sell back to the main power plant when the energy storage is full at the moment.

We assume the total capacity of energy storage is $S_{\max}$, and current storage is S_h with input and output rate of C.

$$S_0 = 0 \tag{4.12}$$

$$S_h = \left\{ \begin{array}{c} S_{h-1} + G_h - x_h, x_h \leq G^h \cap S_{h-1} < S_{\max} \\ \\ S_{h-1} + G_h - x_h, x_h - G_h \leq C \\ \\ S_{h-1} - C, x_h - G_h > C \end{array} \right\} \tag{4.13}$$

We used a discrete time model to represent the local energy storage system. For the energy storage there is a maximum value of the storage, a inout/output rate and current storage level. At time slot 0, we cleared the storage level to be 0. Then with the time forwarding, x^h is the current consumption of time index h, g^h is the total local generation. If the generation g^h is less than the consumption and the energy storage level at last time slot is less than the maximum storage level, then the extra energy goes into the energy storage with the constraint that the extra energy is less than or equal to the maximum input/output rate C. If the extra energy is more than the capacity of maximum energy flow of time h, then only the amount of C energy is stored into the storage.

4.3 Problem Formulation

The goal of the scheduler is to complete jobs while minimize the energy cost and satisfies users' comfort level. The scheduler receives energy price information from retailers, appliance jobs that are entered or scheduled by users, and energy generation from renewable sources. The load scheduling is done one-day-ahead.

The load scheduling problem can be formulated as the following optimization problem:

$$\min \sum_{h=1}^{H} (P_h(E_h - GC_h)) - B_h GB_h \tag{4.14}$$

$$\min \sum_{h=1}^{H} GB_h \tag{4.15}$$

$$\min \sum_{h=1}^{H} GS_h \tag{4.16}$$

Subject to:

$$\sum_{h=Sa}^{Fa} x_a^h = E_a$$

$$\gamma_a^{\min} \leq x_a^h \leq \gamma_a^{\max}$$

$$\sum_{a \in A} x_a^h \leq E^{\max}$$

$$x_a^h \geq 0$$

$$x_a^h = 0, \forall a \in A, \forall h \notin [\alpha_a, \beta_a]$$

$$G_h = GC_h + GB_h + GS_h$$

$$S_h - S_{h-1} \leq C$$

$$T^r_{\min} \leq T^r_h \leq T^r_{\max}$$

4.4 Exhaustive Search Based Optimisation Algorithm

As this is a discrete time non-linear optimisation problem, we propose to use exhaustive search based algorithm to solve this problem. Considering the limited number of energy devices in residential houses and the considerable length of each time slot, Exhaustive search method can produce best optimisation results with acceptable computational complexity.

Algorithm 3 Exhaustive Search Optimisation Algorithm

procedure HVAC OPTIMISATION PROCEDURE
    Initialisation: initial time slot $h = 0$, Set indoor temperature T_0
    for $a_i \in HVAC$ **do**
        for $0 \leq h \leq 71$,do **do**
            for each possible power level $x_a \in X_a$,do **do**
                Calculate the temperature T_h^r
                if $T_{\min}^r \leq T_h^r \leq T_{\max}^r$ **then**
                    Calculate cost C_{total}
                    Compare C_{total} with previous one, keep the lower one.
                end if
            end for
        end for
    end for
end procedure
procedure CONTROLLABLE LOAD OPTIMISATION
    for $a_i \in Controllable$ **do**
        for $0 \leq h \leq 71$,do **do**
            for each possible time slot $h_a \in [\alpha_a, \beta_a]$,do **do**
                Calculate cost C_{total}
                Compare C_{total} with previous one, keep the lower one.
            end for
        end for
    end for
end procedure

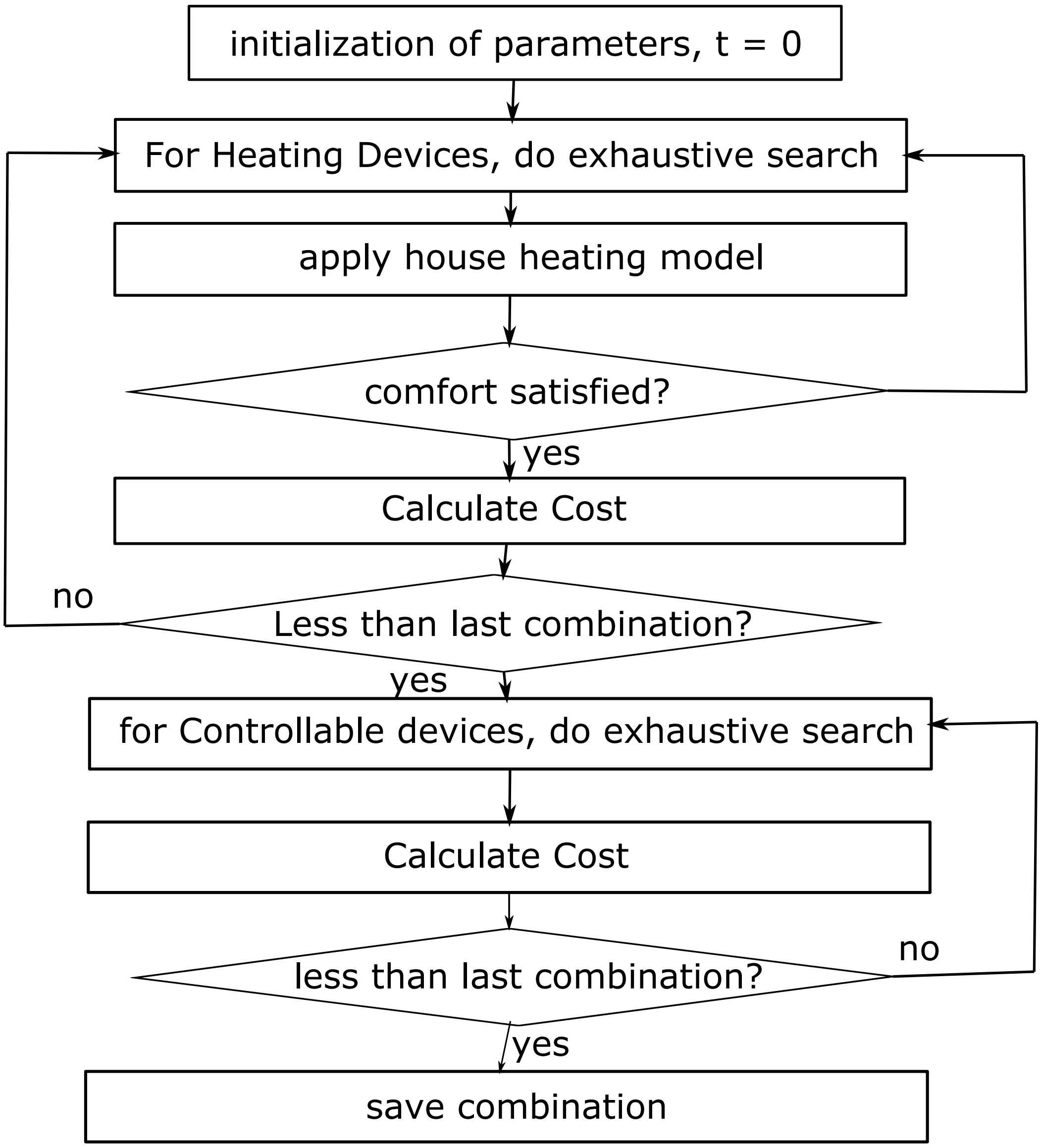

Fig. 4.1 Workflow of Exhaustive Search Optimisation

4.5 Simulation Results

We consider a typical household with HVAC and 4 different controllable loads, whose parameters including their operation windows are summarised in Table 4.1. We divide one hour into 2 equal time slots, each of which is 30 minutes. The maximum power limit of each time slot is set to be 2 KWh. The possible operation power levels of the HVAC system are

Table 4.1 Parameters of Different Loads

loads	Electrical Vehicle	Washing Machine	Boiler	Clothes Dryer
Power (KW)	2.5	0.25	1.2	2
Starting Time	17:00	11:30	15:00	18:00
Ending Time	5:00	18:00	18:00	19:00

assumed to be $[0, 0.4, 0.6, 1, 2]$ KW. The room temperature is required to fall in the comfort range of $\left[T^r_{\min}, T^r_{\max}\right] = [20°C, 23°C]$

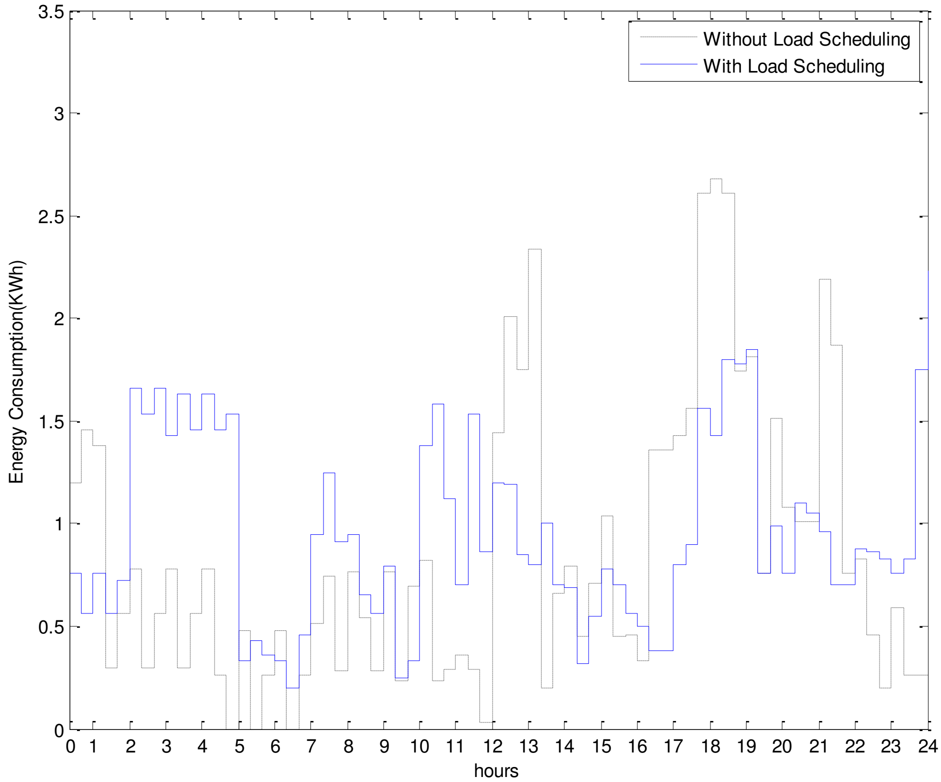

Fig. 4.2 Load Curve on a Domestic Scenario before and after Load Scheduling

The total cost before and after scheduling are £12.75 and £14.71. Reference Prices are: 17.2P/KWh Peak (9:00-21:00) and 6.44P/KWh Off-peak (21:00-9:00). And indoor temperature is all scheduled within the users' preferred range. From figure 4.2, different load curve before and after load scheduling are shown. The blue curve shows lower peak value and total energy consumption than the grey dashed curve. Also, due to the lower electricity price in night time, the controllable appliances like electrical vehicles which consume a lot energy are scheduled to be executed at night time to lower the energy bill. That is why the scheduled average load during night time is higher than the original curve.

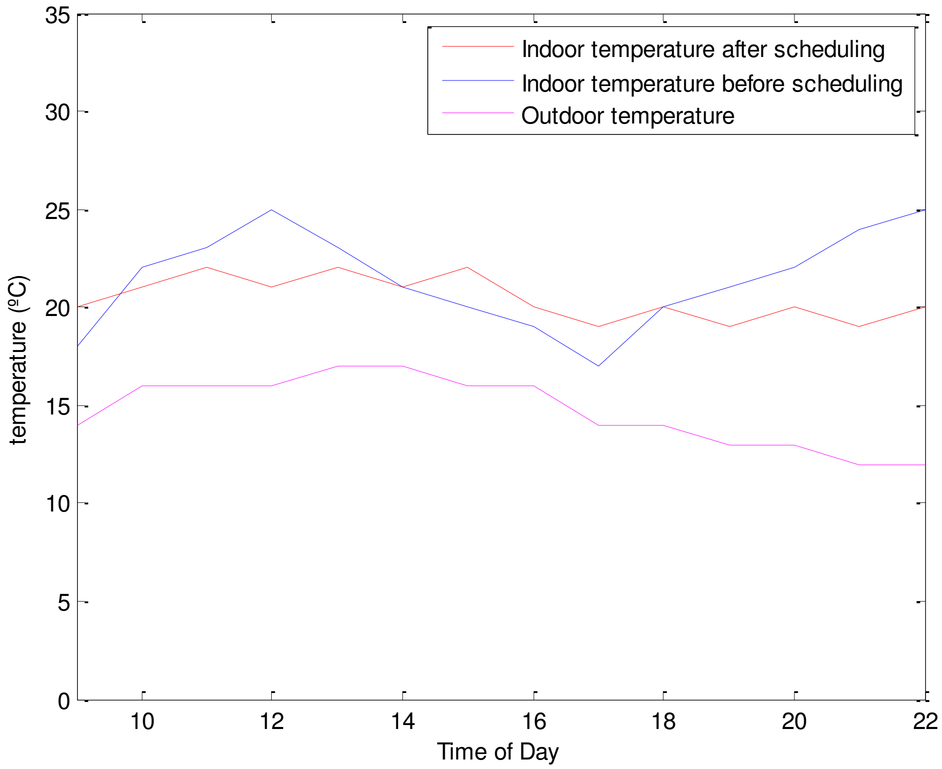

Fig. 4.3 Indoor Average Temperature Before and After Load Scheduling

Figure 4.3 shows the average indoor temperature change before and after load scheduling. Due to the automatic control on heating system and the accurate prediction on indoor temperature flow, the room temperature has a more stable value within users' pre-defined range. As we can see from the figure, the red curve is the temperature flow after load scheduling. Compared to the original temperature flow in the house, because of the accurate prediction on the relationship between temperature and heating output, over-heating and under-heating are prevented. The performance on temperature control of load scheduling is good as it is expected, it achieved the goal of higher comfort level and

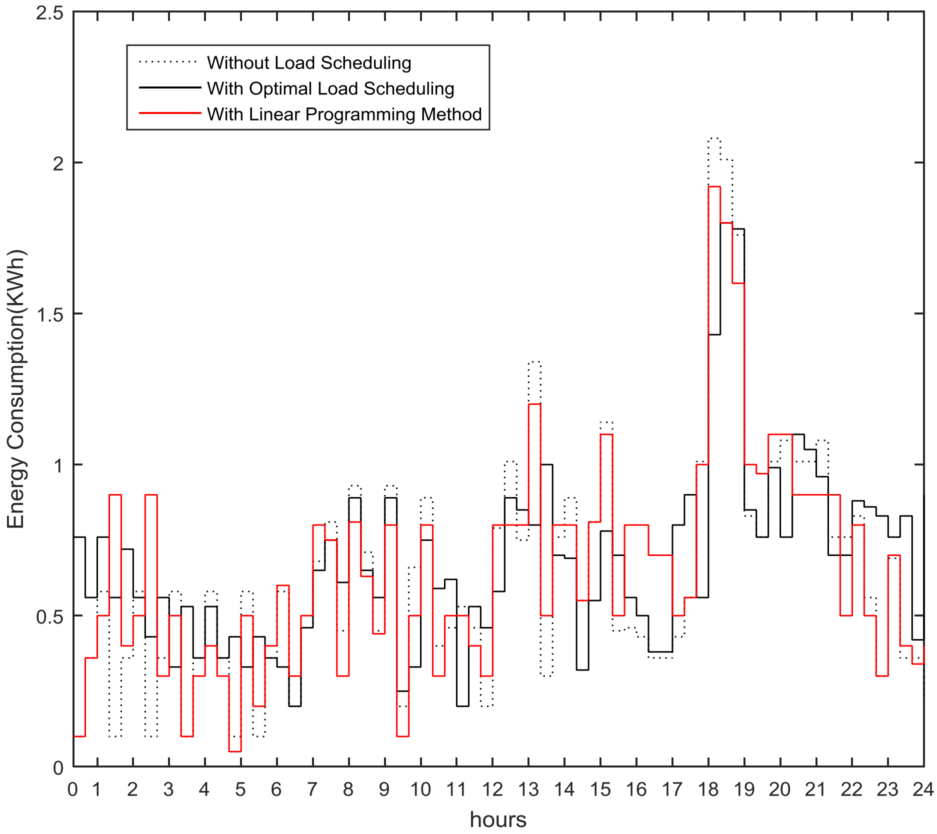

Fig. 4.4 Comparison on different types of methods

Table 4.2 Comparison on Different methods of Load Scheduling

Comparison	Without Load Scheduling	Linear Programming	Exhaustive Search
Peak Load	2.2 KW	1.95 KW	1.7 KW
Energy Consumption	25 KWh	22 KWh	21 KWh
Energy Bill	£4.25	£3.85	£3.7

The algorithm we proposed is considered to be optimal with the problem formulated. From Figure 4.4 we can see that our algorithm has lower peak energy consumption and lower total energy consumption than the result of linear programming. This is due to the through search on solutions of exhaustive search method.

In table 5.1 the comparison on different methods of load scheduling is shown. The secret behind the energy cost saving are firstly, due the the day ahead real time pricing information, we shifted controllable loads to lower pricing period for execution. By this method, we achieved lower cost with no energy reduction. secondly, we scheduled heating controller to avoid over heating of the house, this means we achieved higher user comfort level with even lower energy cost!

4.6 Conclusions

In this chapter, firstly a mathematical model of residential house energy usage devices including energy storage and real-time pricing policy are introduced. An optimisation problem of residential house energy usage is formulated. Then an exhaustive search based method is used to get optimal results. In our simulation, a normal residential house has been modelled. A 2-stage price policy is applied for simplicity. 4 different kind of controllable devices including Electrical Vehicle (EV) are considered for flexible execution operation time. Results shows that through load scheduling for the management of the devices, around 15% total energy savings can be achieved with acceptable user comfort level. Also 10% peak load reduction is achieved within the process. We also confirmed that exhaustive search method achieves optimal load scheduling for residential houses with limited number of controllable devices. Meanwhile the computational complexity is acceptable even with real world devices.

Chapter 5

Web / App Based Building Energy Management System

5.1 Introduction

With the development of computer technology and automated metering infrastructure (AMI), the building industry has got great improvement in past few decades. However, so far there are still a lot drawbacks on existing Building Energy Management Systems (BEMS). Firstly, the existing BEMS are mostly designed for commercial buildings and they do not have the same standard. Also, Non-specialist are not possible to analysis the data collected from smart meters and sensors. That is the reason why most of the land lord make no change to their energy usage even data is available for them [79].

However, domestic buildings energy management has totally different requirements than commercial buildings. First of all, the hardware cost is mostly considered by the land lord.

Then users cares a lot about their daily comfort when they are using the building. Finally, by applying building energy management system, the land lord will need enough savings on their energy bill to accomplish the cost on the hardwares [80].

In this chapter, we firstly introduced some most popular house energy management on the real market including comparison among these products. Then a hardware set called MiHome is introduced as our test platform of house energy management system. An IOS platform based mobile application is development to work with the MiHome system. With real data collected, we proved our proposed house energy optimisation method can work well in real world scenario.

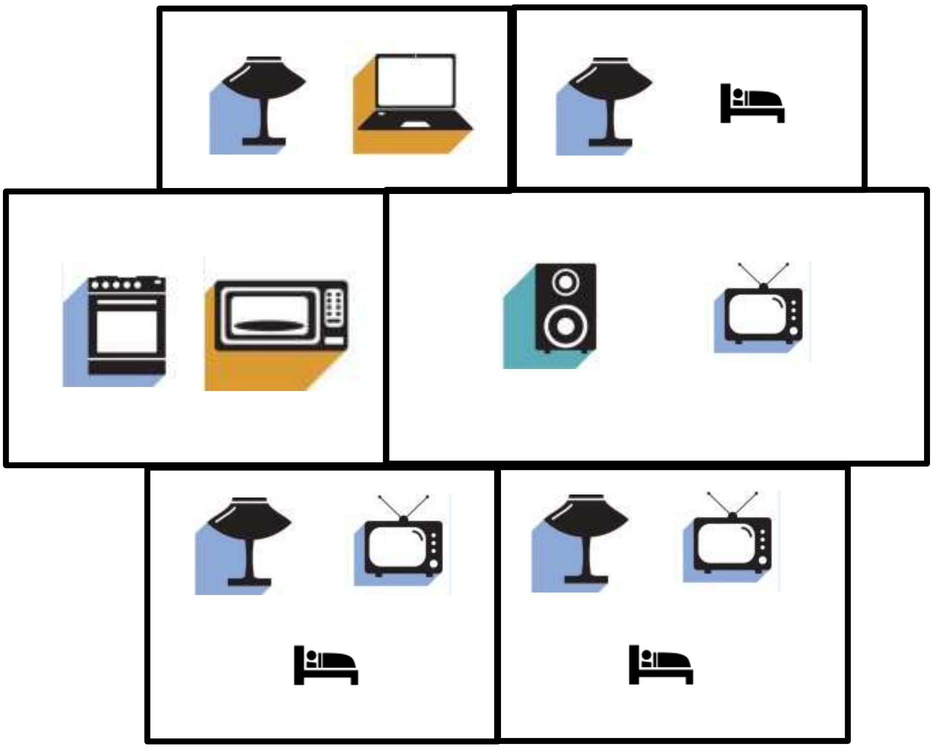

Fig. 5.1 A Domestic Building Scenario

Figure 5.1 shows a common scenario of domestic building, where:

(a) Kitchen is supposed to be much hotter than the other parts while being used.

Table 5.1 List of popular products on the market

Product	Specification	Cost
British Gas Hive	Thermostat Control	£199
Nest	Thermostat Control	£249
Tado	Thermostat Control	£199
Honeywell EVOhome	Multi-zone TRV control	£400
LightwaveRF	Multi-zone TRV control	£359

(b) South part is supposed to be warmer than the other parts, the maximum difference can be over $2°C$

(c) The management on Electrical Vehicle (EV) can have a huge impact on home energy management

(d) The need for watering on the plants depends on the weather condition.

The products available on the market mainly focuses on boiler energy management since it consumes over half of the total energy of the building. Although full home energy management may include Thermostat Radiator Valva (TRV) control also to enable multi-zone temperature control. Google's Nest is considered to be the leading brand on the market. The summary on several popular products is listed below: The functionalities of current products are mostly limited to simple control ability and very limited artificial intelligence. Based on our research, a more intelligent product including hardware and software is developed in our project.

(a) Learning of local parameters (size, temperature difference etc.) to determine the approximate time of the heating/cooling procedure.

(b) Learning of users behaviour and automatically set operation schedule for users to satisfy their preferences.

(c) Intelligent switch on/off boiler according to users' geo-location with mobile APP.

(d) Automatic on/off of TRVs and boiler by detection of human presence in rooms.

5.2 Hardware Setup

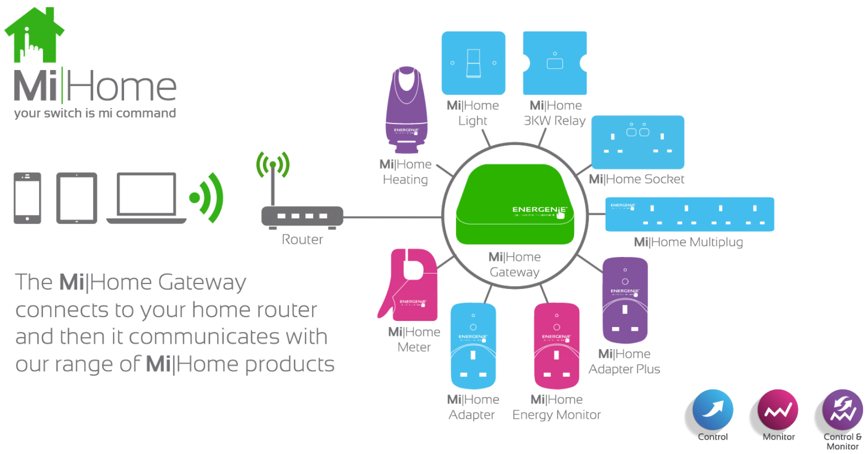

Fig. 5.2 Hardware Setup

Figure 5.2 shows the hardware overview of our test system. From the figure we can see that all the control abilities are enabled by the remote controllable plug-ins. There are all kinds of plug-ins available for all kinds of electricity devices. All these devices talk to MiHome gateway with 433 MHz frequency signal. the coverage is around 50 meters which is quite enough for most of the residential houses. MiHome gateway is a Raspberry Pi based micro-computer which has ethernet connection. Mobile devices can access the data and control the registered devices from anywhere. Our APP provides Graphical User Interface (GUI) and advance control functions for end users. Figure 5.3 shows the gateway used in the

Fig. 5.3 Raspberry Based Gateway
[81]

test platform which can be treated as the brain of the system. All other devices are connected to this device with 433 MHz RF signal. Then it is linked to the internet using regular ethernet connection. The range of this device is around 50 meters so depends on the size of the house, one or more gateway are needed. Figure 5.4 shows the remote controllable devices which takes place of the original ones. All these devices can be used to monitor and control the energy usage. Figure 5.5 shows the TRV we used in our project. It can be used to replace the original TRVs on the radiator (may need adaptor for different types of traditional TRVs). This opponent can ensure the capability to control the temperature of each individual room in the house to reach higher energy efficiency and higher comfort level.

Fig. 5.4 Wall Sockets and Plug-ins
[81]

Fig. 5.5 Smart Thermostat Radiator Valve (eTRV)
[81]

5.3 Data Analysis

Evolving technologies in the energy and utilities industry, including smart meters and smart grids, can provide companies with unprecedented capabilities for forecasting demand, shaping customer usage patterns, preventing outages, optimizing unit commitment and more. At the same time, these advances also generate unprecedented data volume, speed and complexity. To manage and use this information to gain insight, utility companies must be capable of high-volume data management and advanced analytics designed to transform data into actionable insights. For example, designing effective demand response programs requires that utilities execute advanced analytics across a combination of data about customers, consumption, physical grid dynamic behavior, generation capacity, energy commodity markets and weather.

But the possibilities don't end there. With the additional information available from smart meters and smart grids, it is possible to transform the network and dramatically improve the efficiency of electrical generation and scheduling. However, the new mix of resources available requires more granular forecasting, load planning and unit commitment analysis than ever before to avoid inefficient energy trading or dispatching too much generation.

Data storage costs can explode due to increased data volumes and retention requirements if organizations are using traditional, relational database technologies. Additionally, report generation and analytics can become painfully slow due to high volumes—companies may not be able to load and analyze all of the information fast enough to support decision making. Applications begin to drag and IT may struggle to meet service-level agreements.

Data Processing Flow

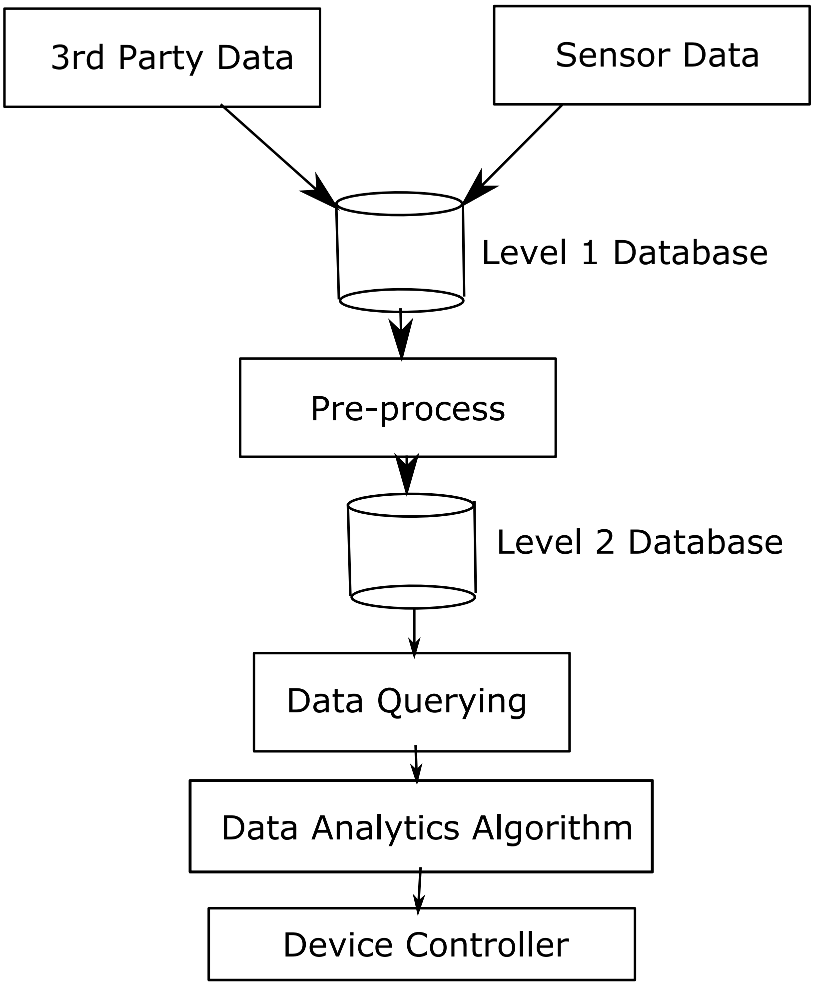

Fig. 5.6 Data Processing Flow

Figure 5.6 shows the database structure and the data processing flow of our system. Due to the huge volume of data points incoming to database (about 1 million data points everyday), if all raw data are stored in the database, it will be extremely hard to query through database of this size. So a preprocess on raw data is needed to combine/structure the raw data into some meaningful patterns and stored in a higher level database for further data process algorithm (machine learning etc.) and those processed data are passed to smart home controllers.

5.4 Test House

We also have set up a normal residential house as our test house which has average level energy consumption. This house belongs to a family of two adults and two children. The test duration is two months from November to the end of December of 2015 as shown in figure 5.7.

Fig. 5.7 Test House

Figure 5.8 shows the TRV readings of the house. As we can see, it shows the target temperature and current temperature of the TRVs. TRV1 is the temperature of bedroom on the first floor and TRV11 is the bedroom on the second floor. TRVout shows the temperature of outside as reference.

Fig. 5.8 TRV reading

Figure 5.9 shows the monitoring and controlling interface of the home appliances. Timers and historical data are available to the users. Also the users can switch on/off very easily.

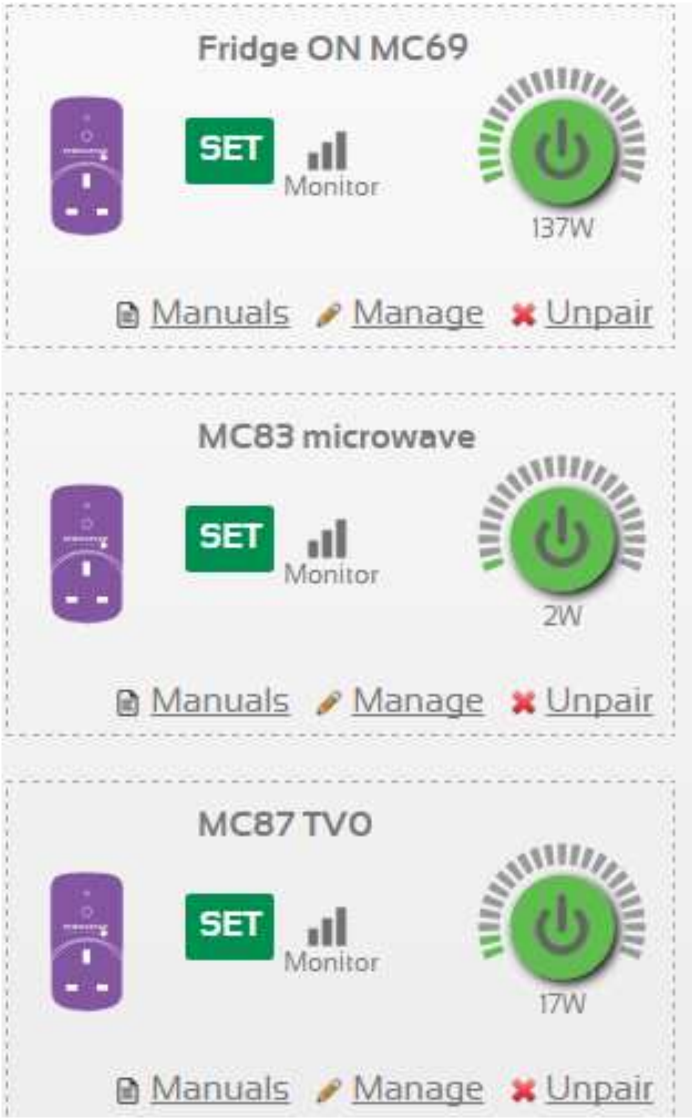

Fig. 5.9 Home Appliance Control and Monitor

Figure 5.10 shows the interface of Appliances. From the figure, current usage and historical usage are graphically displayed clearly. There are also prediction of the total cost of that device based on trend of usage.

Fig. 5.10 Monitoring Interface of Appliances

Drawback of Current Testing Products

1. The historical Data is limited to a fixed period of time. From figure 5.10, the historical energy consumption data is displayed as graphics but with only limited time period of usage.

2. Graphical control is not user-friendly: the graphical control is just plain controls but without advanced functions.

3. No advanced energy management services available from the current system.

5.5 Prototype of New APP

Figure 5.11 shows the users preference learning interface of our APP. Once the user switch on/off a device, APP will automatically create a schedule for that device in the future so users do not need to set that again.

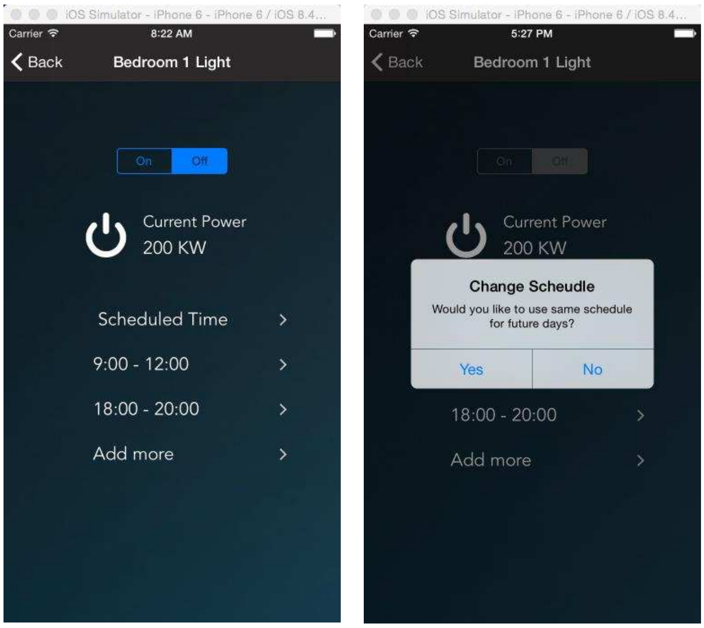

Fig. 5.11 Users' Preferences Learning

Figure 5.12 shows the heating management interface of our APP including the heating time prediciton functionality. According to user's historical data and real-time weather condition, our self-learning algorithm calculates the approximate time to heat/cool the room to target temperature. Users can easily get desired temperature once they arrived home.

Figure 5.13 shows a figure in the APP which gives the total energy consumption curve of the house before and after automatic load scheduling control. This function is only enabled when automatic control mode. System will automatically run the schedule predefined by users to save money for them.

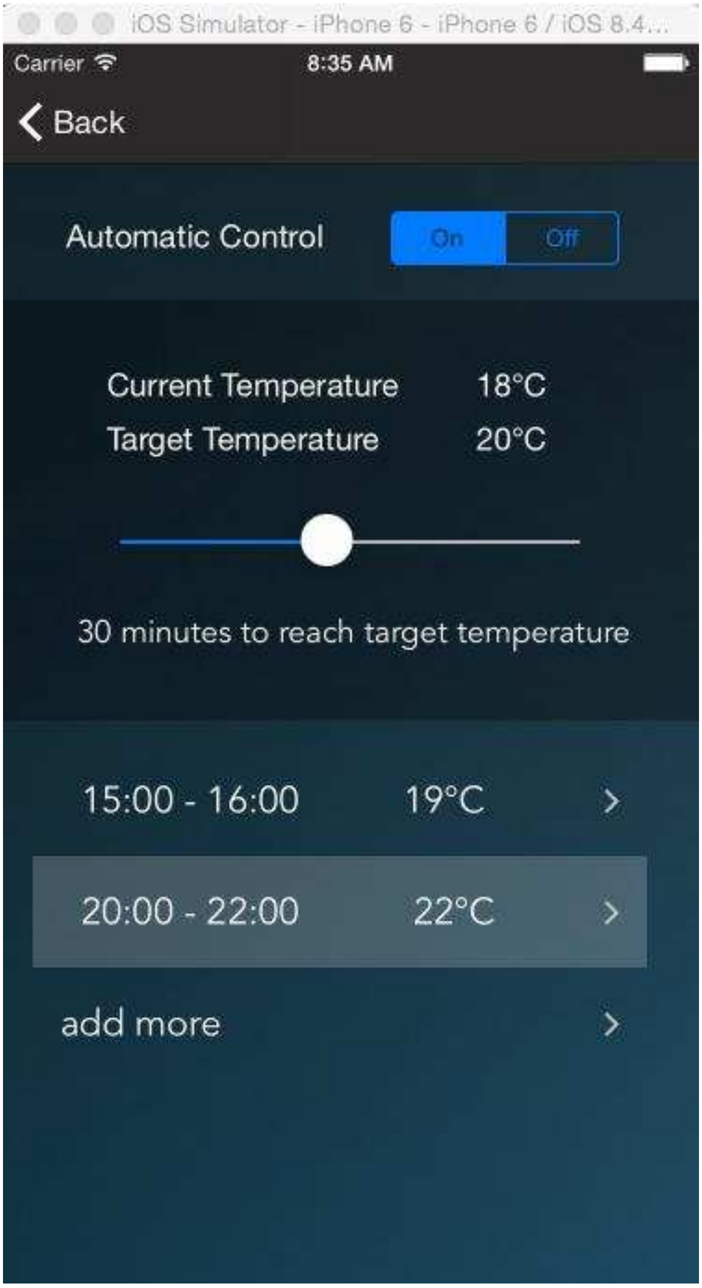

Fig. 5.12 Environment Learning

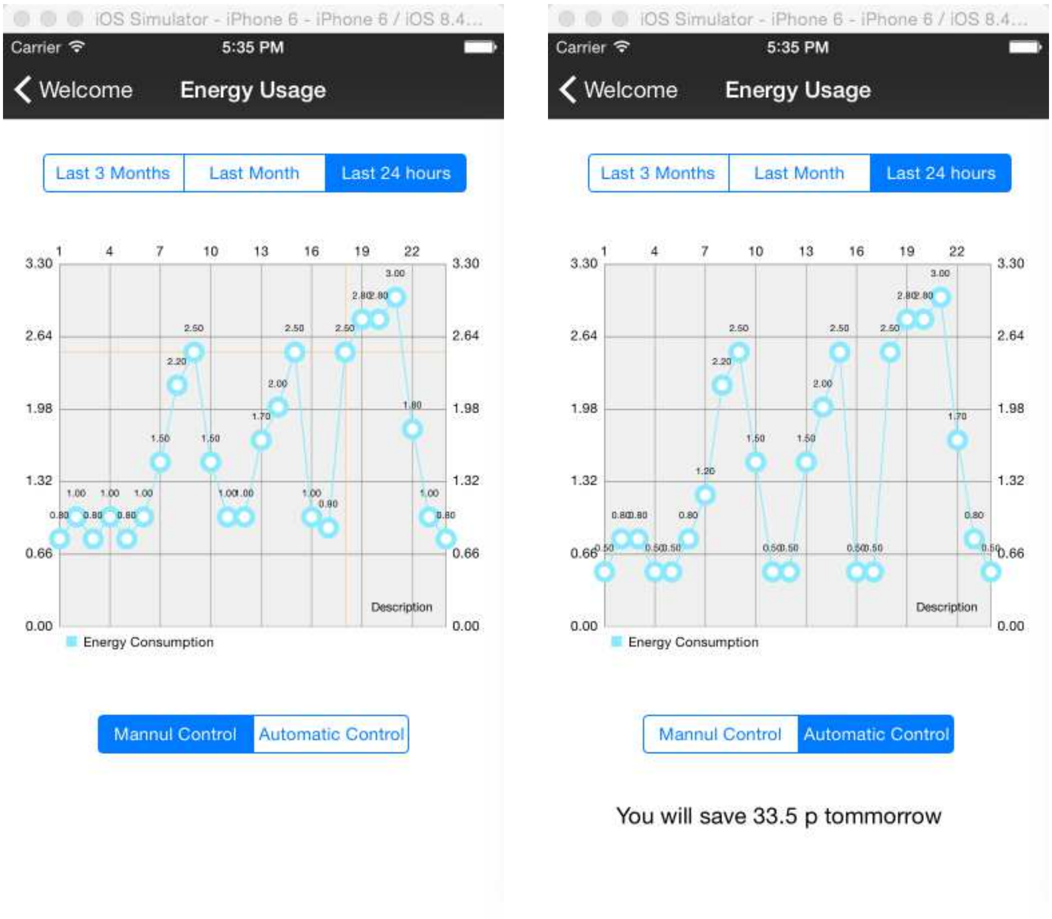

Fig. 5.13 Automatic Control

Chapter 6

Conclusions

Our project developed an energy management system for residential houses and small commercial buildings. It covers all possible energy consumption optimization. Software is still under development and hardware test is still under way. We did a series of researches and products to formulate a whole home area energy management system with potential commercial value.

First of all, a discrete time temperature-to-time building thermal model is proposed with multiple heating resources considered. Artificial neuron network based machine learning algorithm is developed to predict the room temperature change according to the collected historical data together with forecast data.

Also, an optimal load scheduling algorithm is developed to minimise the energy cost for users and at the same time satisfies their comfort level. This algorithm takes day-ahead pricing from energy retailers and similar day energy consumption data into account. Users can predefine their preferred indoor temperature and appliances execution time. This algorithm achieves its optimality by formulating a genetic algorithm based method that can solve the optimisation problem efficiently. This algorithm is designed for home area energy consumers with low energy efficiency. The result shows it has achieved higher energy efficiency than previous method. The average energy consumption of a residential house per day is 20 KWh. We assume these energy are generated by main sources which response to 10 Kg of CO_2 emissions. Millions of tons of CO_2 emission will be reduced due to the overall reduced energy requirement and peak load requirements. Secondly, we proposed a machine learning based algorithm based energy usage and heating time prediction method. Through this method, the time for the room to be heated can be accurately predicted based on historical data. Also, the amount of energy that consumed to heat the room can be calculated so the load scheduling can be much more precise. The results have been obtained using the data coming out of our test house located in Liverpool. Thirdly, a web-app based practical solution has been developed to become a potential commercial product of BE Thinking Ltd. Research and test on the effectiveness of our product has been tested with both computer simulation and practical environment test house. The feedback from the users has shown that our product shows some unique features from the existing products on the market including users' preference learning and automatic energy management suggestion etc.

By applying our algorithm, the total energy consumption is reduced by 15%, which is 16 KWh per house per day. This adds also 2 Kg of CO_2 emissions per house per day equivalently. In addition to this, due to the reduction on peak loads, there will be a significant CO_2 emission reduction because of the cut on overall generation.

Future Work

During the implementation with real devices with real customers' data, a shortage has been found out which indicates the limitation of this heating prediction method. Some heating device may not even been turned on for a long time, which results in lack of training data for the device. It is not precious prediction with missing training data. Therefore, in the future, we intend to develop a self-training run of devices to produce the desire training data from real environment to avoid lack of training sample.

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